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THESIS

AN INTELLIGENCE COLLECTION MANAGEMENT MODEL

by

Thomas A. Gandy

June 1984

Thesis Advisor:

S.H. Parry

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An interactive multiattribute decision aid useful in the prioritization of numerous collection requirements is demonstrated.

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An Intelligence Collection Management Model

by

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Captain, United States Army
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Submitted in partial fulfillment of the
requirements for the degree of

MASTER OF SCIENCE IN OPERATIONS RESEARCH

from the

NAVAL POSTGRADUATE SCHOOL
June 1984

ABSTRACT

This thesis examines the structure and functions of a generalized tactical intelligence collection system. Included are its position in the intelligence system structure, relationship with other activities in the intelligence system, and the organization and control of its components. A mathematical optimization model of a simplified intelligence collection system is developed to explore several issues related to intelligence collection. An interactive multiattribute decision aid useful in the prioritization of numerous intelligence collection requirements is demonstrated.

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I. INTRODUCTION

A great deal of effort has been expended in recent years concerning the management of large quantities of battlefield intelligence information. The presumption of such concern is that vast amounts of information will be collected during the course of the future battle. The deployment of numerous collection platforms, sensors, and the like does suggest that there will indeed be a deluge of information. But will this information be of value to the decision maker?

One way to insure that collected information is of value is to manage those collection platforms in an intelligent manner. This implies that their operation should be controllable and efficient. This thesis will develop the physical and functional structure of a generalized intelligence collection system with the idea in mind of improving the control and efficiency of its collection platforms. It will analyze the components of this collection system to determine where modern management tools can be applied to the collection management process.

Chapter Two introduces the generalized intelligence system structure and describes the relationships between its major subsystems - the requirements system, analysis system, collection system, and dissemination system. It additionally highlights the role the intelligence requirement plays in the intelligence system. Chapter Three focuses upon the intelligence collection system to include its structure, functions, and considerations which make the effective management of the system such a difficult task. Chapter Four analyzes the critical component of the collection system - the intelligence collection requirement - in great detail. It focuses upon the sources of the collection

requirement and the traditional flow and management of the requirement in the collection system. Chapter Four additionally develops a more analytical manner in which collection requirements can be decomposed into smaller elements and, based upon this process, suggests a restructuring of the traditional collection system. Chapter Five develops a mathematical optimization model of the collection management process and explores variations of that model which are useful in the understanding of the collection management problem. Chapter Six illustrates how the models developed in the previous chapter can easily be modified to the realistic collection management environment. Finally, Appendix A demonstrates a multiattribute decision making approach toward the prioritization of collection requirements according to current or envisioned battlefield conditions.

II. A GENERALIZED INTELLIGENCE SYSTEM

A. INTRODUCTION

Any tactical intelligence system can be described in terms of its major functional systems. These systems include the following:

- Requirements System
- Analytical System
- Collection System
- Dissemination System

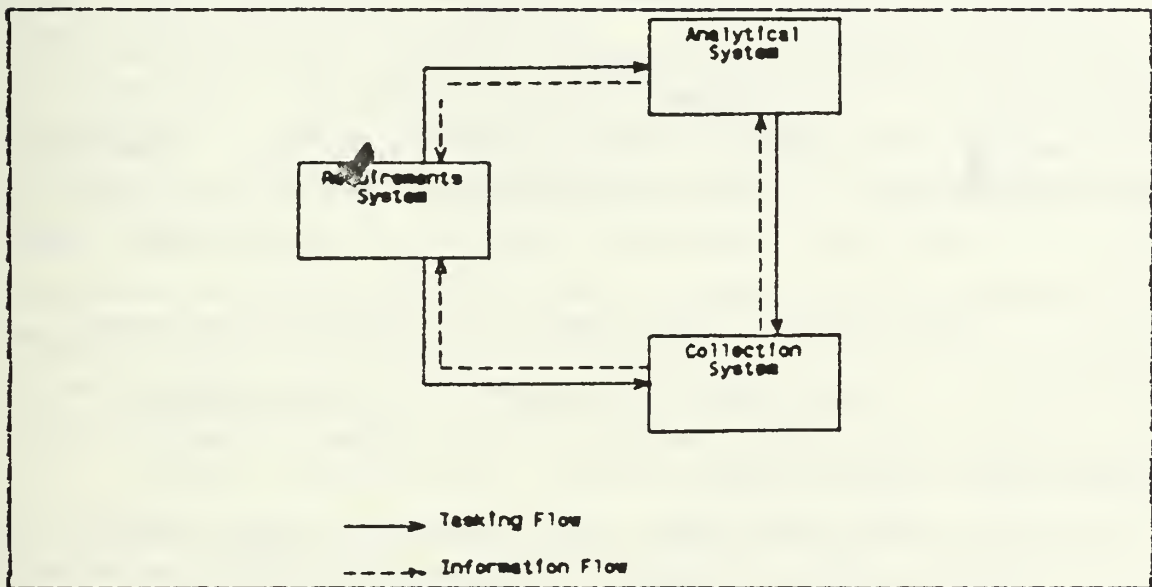


Figure 2.1 Generalized Intelligence System.

The focus of this chapter will be to examine some of the generalized characteristics of the first two of the systems listed above. Because of its key role in the collection and

analytical process, particular attention will be paid to the generalized requirements system. A detailed analysis of the collection process and system will follow in the remaining chapters of this study. Therefore only fundamental considerations of that process as it relates to the analytical and requirements systems will be addressed in this section. The analytical system, though critically important to the overall intelligence process, will only be addressed as it relates to a collection system - the primary subject of the thesis. The dissemination system will not be specifically addressed due to its relationship and identification with the type of communication system employed by the intelligence system. The other two systems, however, are more easily isolated from the specific aspects of the communication system and will be discussed.

Figure 2.1 depicts the functional relationships formed between the three major components of a tactical intelligence system. Intelligence requirements are generated by the users of the system - subordinate units, staff elements, and the commander. These requirements can be satisfied in one of three ways - through analysis, collection, or a combination of the two. The requirements and analysis systems both task the collection system for intelligence information. The collection system primarily responds to such tasking and rarely would task the other two systems for substantive information.

The following paragraphs will address topics related to this general structure and its functions in a more detailed manner.

B. REQUIREMENTS SYSTEM

A requirements system must be able to accomplish three basic tasks:

- Receive intelligence requirements from users.

- Identify the nature of the requirement with respect to the capabilities of the particular intelligence system.

- Task the proper functional subsystem(s) of the intelligence system for satisfaction of that requirement.

The first of these requirements is not related to the topic of this thesis. The other two, however, are more interesting and will be addressed. It is important, prior to beginning this discussion, to first understand the complex nature of an intelligence requirement.

An intelligence requirement is a representation of a user's need for information concerning the disposition, capabilities and intentions of his enemy. Clearly, this definition is quite broad and necessarily subjective in nature. More specific definitions of an intelligence requirement are difficult to express. Enumeration of all previously identified and envisioned requirements is impractical (and probably impossible). It is possible, however, to classify intelligence requirements into functional categories. This classification scheme will eventually allow for a more precise representation of an intelligence requirement.

C. THE CLASSIFICATION OF INTELLIGENCE REQUIREMENTS

1. Requirements as a Function of Objective

Every intelligence requirement has an objective. For the most part that objective is to determine or clarify some enemy related characteristic which at the present time is not satisfactorily defined. The requirement objective may be related to enemy capabilities. This, in turn is related to the type of enemy force or concern - armor, artillery, chemical, air defense, etc. A requirement objective may also be related to enemy disposition. In this case concern would be directed toward the spatial orientation of

enemy units on the battlefield. Targeting information, for example, forms a class of intelligence requirements whose objective is related to enemy disposition. Requirements related to first or second echelon forces are also disposition oriented. Other requirement objectives are related to enemy intentions. These requirements are generally more subjective in nature and, hence, their eventual satisfaction depends upon an understanding of enemy tactics and doctrine.

The point to be made is that an objective is one factor which all intelligence requirements have in common. Although it may be impossible to enumerate all possible requirement objectives, it is possible to relate each requirement objective to either the analysis or collection activities. This capability is important and will allow for a greater development of an intelligence collection model in this thesis.

2. Requirements as a Function of Time

The value of intelligence information is often closely related to time. Some types of information are of value only for a short period of time. Tactical targeting data is an example of such information. Other types of information can be of value for greater lengths of time. Information concerning the communications structure of the enemy may be of value until his next frequency change. Thus, an intelligence requirement related to some form of information will have associated with it some temporal relationship or function. Normally this relationship identifies a given requirement as either short or long range in nature. This temporal relationship is critically important and will be discussed throughout this study.

3. Partially Satisfied Requirements.

Some requirements may, after a first effort by the intelligence system, be only partially satisfied. In this situation the following points must be considered:

a. Extent of User Satisfaction

The extent of the user satisfaction/dissatisfaction with the partially satisfied intelligence requirement is important for two reasons. The most important is that of determining whether or not the requirement should be replaced into the system. If the level of dissatisfaction was absolute then it might be wise to consider resubmission. However, if the dissatisfaction was less severe, then resubmission of the requirement may be unwise. The second reason this consideration is important deals with improvement of the requirements system. Any system must know when its performance is unsatisfactory if it is to have any chance of long range success. Information concerning the extent of user satisfaction therefore is useful in that it provides the collection system operator with feedback concerning the performance of his system.

The existence of partially satisfied requirements in the intelligence system suggests that some procedure for reinsertion of these requirements should (if that action seems suitable) exist. At a minimum an analyst should be aware of the existence of such requirements and consider their impact on the intelligence process and methods of dealing with that impact.

b. Requirement Validity

The requirement may or may no longer be valid. For instance, the initial informational requirement may be such that delayed or subsequent satisfaction would be of

little or no use to the user. In this situation it would not be wise to resubmit the requirement into the system for satisfaction.

c. Partial Requirement Validity

The requirement may be partially satisfied and therefore only partially valid. In the event some version of the original demand still exists, then that subset of the original demand (or requirement) might be replaced into the intelligence system for further action.

4. Maintenance Requirements

Some requirements are generated by the intelligence system itself. These can be thought of as overhead costs which must be expended to maintain the system. These requirements are sometimes referred to as collection or analytical management requirements.

5. Priority of Requirements

Each class of requirements may also be defined in terms of its relative importance at a given time during the battle. This relative requirement importance will be referred to as priority. The source of a requirement's importance could be any number of things. Some of these include its relationship with the user unit or organization, its relationship to the enemy, or perhaps its relationship to a certain location of interest on the battlefield. The result of this secondary form of requirement classification, from a modeling point of view, is added complexity. This is particularly true with respect to determining the functional relationships between different classes of intelligence requirements. For example, is a long range requirement of medium priority less important than a maintenance requirement of high priority? This relationship is difficult to

describe and is handled best when broken down in a bit more detailed manner.

The previous discussion leads to the following functional representation of an intelligence requirement. It can be defined in terms of its relationship with objective, time, and priority.

$$\text{Requirement} = \int (\text{objective, time, priority}) \quad (\text{eqn 2.1})$$

Maintenance requirements are treated as a special subset of the generalized intelligence requirement and partially satisfied requirements are treated as scaled down versions of regular intelligence requirements.

D. FUNCTIONS OF A REQUIREMENTS SYSTEM

Based upon this brief introduction to the types of requirements which are associated with a tactical intelligence system it is now possible to address the functions a requirements system must perform. Figure 2.2 is a functional schematic of a generalized requirements system. The discussion which follows addresses each major portion of this system.

1. Definition and Categorization of Requirements

In this section of the requirements process general intelligence requirements which enter the system from users are more clearly defined. In particular, the objective of the requirement is clearly outlined. Additionally, the justification for the intelligence information should also be determined at this time. From this clarification process each intelligence requirement can be categorized according

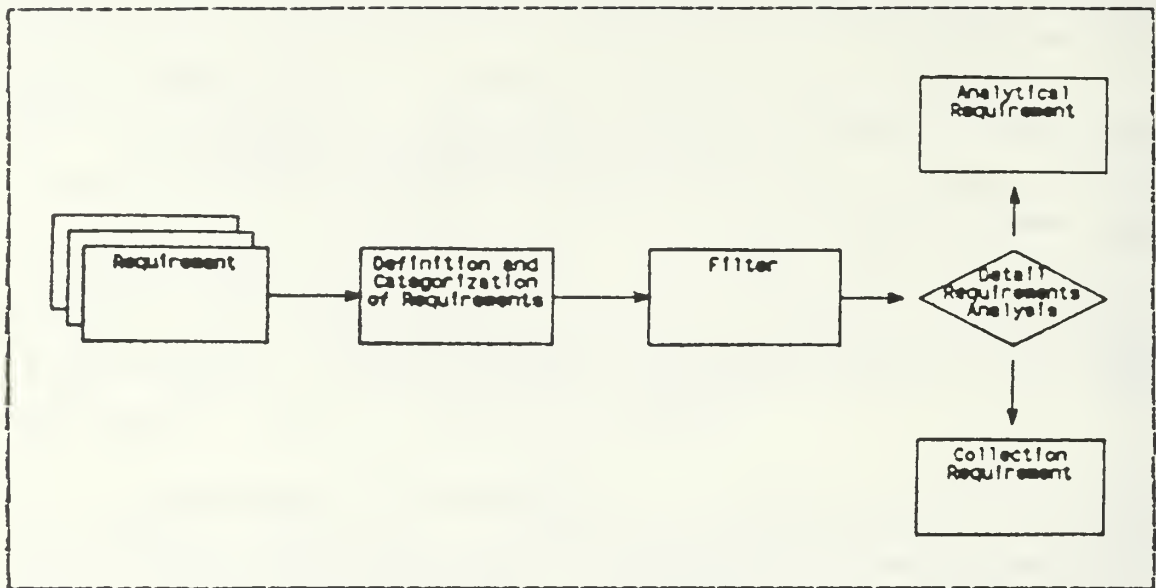


Figure 2.2 Requirements Process.

to each functional parameter mentioned in the preceeding discussion. These are addressed below:

a. Requirement Objective

The objective of the requirement should be specifically determined. Not only should the major objective classification (disposition, capability, or intention) be identified but also any identifiable subclassifications which might provide insight into the nature of the objective. Examples of such subclassifications include the ultimate use of the intelligence information (operations, terrain analysis, targeting), the types of enemy forces the user is most interested in, etc. The ultimate purpose of this section is to provide as much information as possible to the intelligence system concerning the nature of the requirement objective.

b. Time

At this point in the process the purpose in evaluating the time parameters of the requirement is simply to determine whether or not any special handling of the requirement is necessary due to its possible short suspense time.

c. Priority

The requirement priority should be checked for suitability. Any possible definitional priority errors should be clarified. For instance, it may be that for a given military unit the standard procedure is to classify a certain type of intelligence requirement as low priority. This process should be able to detect if such a type requirement were submitted at an improper level of priority and, subsequently, properly classify the requirement. It should be noted that the priority a user requests to be associated with his requirement may not correspond to that requirement's ultimate priority in the intelligence system. The ultimate priority is determined by a variety of factors (addressed in the next section) which the user may or may not be aware of. Normally the priority a user identifies with his requirement serves primarily as a flag in the event special handling is required. The user's priority, however, should reflect the importance he places on that requirement with respect to his other requirements.

In addition to the above it should also be determined whether or not the intelligence system can actually respond to such a requirement (some requirements are simply impossible to satisfy). This determination is referred to as gross suitability and will be addressed, with respect to the collection system, in later chapters.

Once the intelligence requirement has been redefined with respect to the parameters discussed above it would, under normal circumstances, progress through the filtering process described in the next section. If, however, it was determined from this defining process that immediate or special processing of the requirement was called for then it should be possible for the requirement to bypass the filtering process. Thus, in some cases the initial processing of the intelligence requirement (definition and categorization) can also be thought of as a coarse filtering process.

2. Filter (Prioritization of the Requirement)

A filtering process must basically accomplish two functions. It should determine if the requirement can be satisfied with information already on hand or is being worked on by the system even though the information may not actually be on hand. If so, then the normal procedure would seem to be to immediately provide the user with the appropriate information. The implications of this seemingly simple transaction are great. It implies that there is (or should be) an effective interface (information access) between the requirement filtering process and the primary intelligence data base. If the requirement can be satisfied with information already on hand then it would seem reasonable to forward that information to the appropriate users.

It should also determine whether or not a requirement which cannot be satisfied with on hand information will be satisfied (and at what level of effort) through tasking of the intelligence system. This is the heart of the prioritization process and as such can become quite complex. Requirement prioritization is basically a function of some of the following factors:

a. Command Guidance

Obviously this is the most important input into the filtering process. It is expected (and experience shows) that this guidance is fairly general in nature and for the most part follows the dictates of current plans and operations. More specifically, we can expect the commander to be concerned that friendly units involved (or soon to be involved) in combat operations receive the proper amount and quality of intelligence support. He would also be concerned that all significant threats to the well being of his unit are identified and understood. When intelligence resources are scarce the commander's guidance also serves in an important de facto resource allocation role.

It should also be noted that as any combat situation changes the nature of command guidance might very well change. This consideration indicates a need for an intelligence system to be flexible enough to respond to any envisioned changes in command guidance.

b. Criticality of the Requirement

Certain types of intelligence will almost always be of greater importance to the unit than others. Normally, these types of information are of potentially great threat to the unit or of extreme importance to the outcome of the unit's mission. An example of high threat information might be that related to the enemy's current capability to deliver nuclear weapons. Information of high importance might be that related to the enemy's command and control structure. It should be noted that the potential importance of a requirement could easily be described as a dynamic process with respect to the conduct of the battle. For example, intelligence concerning a nuclear capable missile with a range of 100 kilometers becomes more and more important as

that missile moves from rear areas to forward positions on the battlefield.

c. Answerability of the Requirement

Some requirements simply cannot be addressed by the system. A time sensitive (i.e. the information is needed quickly) yet legitimate requirement (legitimate in the sense that the system under normal circumstance would and could respond to such a requirement) may be unanswerable due to the limitations of the intelligence system itself. Similarly, an overly detailed requirement may also be beyond the capabilities of the system. The following intelligence system responses to this type of requirement can be envisioned.

- Reject the requirement outright.
- Pass the requirement forward to higher or lower units for possible satisfaction.
- Negotiate the specifics of the requirement with the user to determine if one or more of the restraints can be relaxed.

d. Quantity of Users

The stresses on the system, both from a management and resource allocation point of view, increase with the presence of more users in the system. It is expected that these demand related stresses would be clearly reflected in the filtering process. In particular one would expect that requirements not fitting into a certain mold of acceptability would have less chance of passing unhindered through the filter during periods of heavy demand rather than light demand. Thus, it becomes clear why the initial definition of the requirement process is very important. It helps to insure that a user generated requirement is

described in terms the requirement filtering process can understand.

e. Time

This is one of the most important and complicated of all priority parameters. The following paragraphs describe some of the time related concepts which relate to the filtering process of the requirements system.

Many organizations in a given unit have similar intelligence needs. As a result, often identical (or nearly so) intelligence requirements are placed into the intelligence system. To limit the waste associated with this type of problem the intelligence system periodically prepares reports of common interest. Numerous (primarily routine) intelligence requirements can be satisfied through the publication of timely periodic intelligence reports. The publication of such reports should thus have some effect on the requirements filtering process. Specifically, the timing of these reports will be of some importance. For instance, requirements submitted into the system which one can expect will be reasonably well satisfied (from a timeliness and quality of information point of view) with a soon to be published periodic report should probably be rejected with the caveat that the information will soon be forthcoming. Of course, measures must be taken to insure that the requested information does eventually get to the user whose requirement was initially rejected.

An additional aspect for consideration with respect to the publication of such reports is that of resource allocation. The publication of periodic reports places a drain on the capability of the intelligence system similar to the type of drain placed on it by excessive quantities of users. Thus, there is a cost associated with the production of such reports. This cost should be defined and reflected in the filtering process.

One can look at the publication of periodic reports as an action which decreases the requirement load on the intelligence system (by making the filtering process more stringent) while the resources allocated in preparation of the intelligence reports can be looked upon as an action which increases the stress on the intelligence system (by reducing the resources available for the satisfaction of requirements). A good balance between value and cost must exist if periodic reports are to be useful to the intelligence system.

On occasion, requirements can conflict with ongoing collection operations. This is similar to the consideration addressed above. During certain types of intelligence operations one can expect that nearly all (or some significant portion) of available intelligence resources might be employed. At these times it is possible that many valid intelligence requirements which might disrupt an ongoing intelligence operation may not be satisfied. The point to be made is that the failure to address the valid requirement is not necessarily due to the overall lack of resources available but rather the fact that the specific requirement, from a temporal point of view, has come into conflict with an ongoing (resource draining) intelligence operation. At any other point in time it is conceivable that the same requirement may have been satisfied. Therefore, the timing of intelligence operations (in particular the scheduling of such operations) is possibly an important input parameter to the requirements filtering process. This difficulty can be limited by interfacing with the appropriate users to determine if delays in satisfaction of the requirement might be somewhat acceptable.

There exist time delays associated with the production of certain forms of intelligence. These time delays, when contrasted with the time constraints of a

particular intelligence requirement itself, may not allow for the satisfaction of the requirement. Such delays may come in the form of a lead-time delay (applicable in certain scheduled types of operations or in operations which require a certain amount of warm-up time prior to producing intelligence), and lag-time delays (applicable in the situation in which the requirement time restraint is shorter than the resource time restraint - thus information produced to satisfy the given requirement will be late (and probably less than optimal)).

The filtering process must therefore be able to compare two classes of time restraints - those associated with the user's actual intelligence requirement and those associated with the intelligence system. Figure 2.3 outlines this time analysis process.

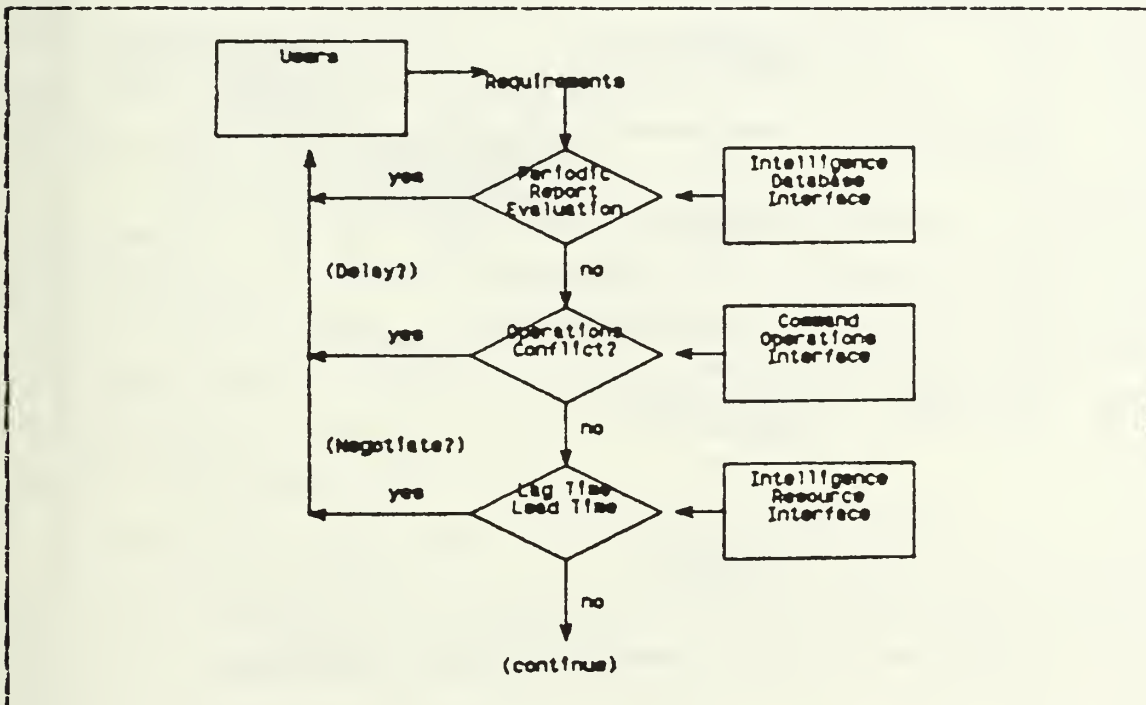


Figure 2.3 Time Analysis.

Figure 2.4 outlines the flow of a requirement through the entire filtering process.

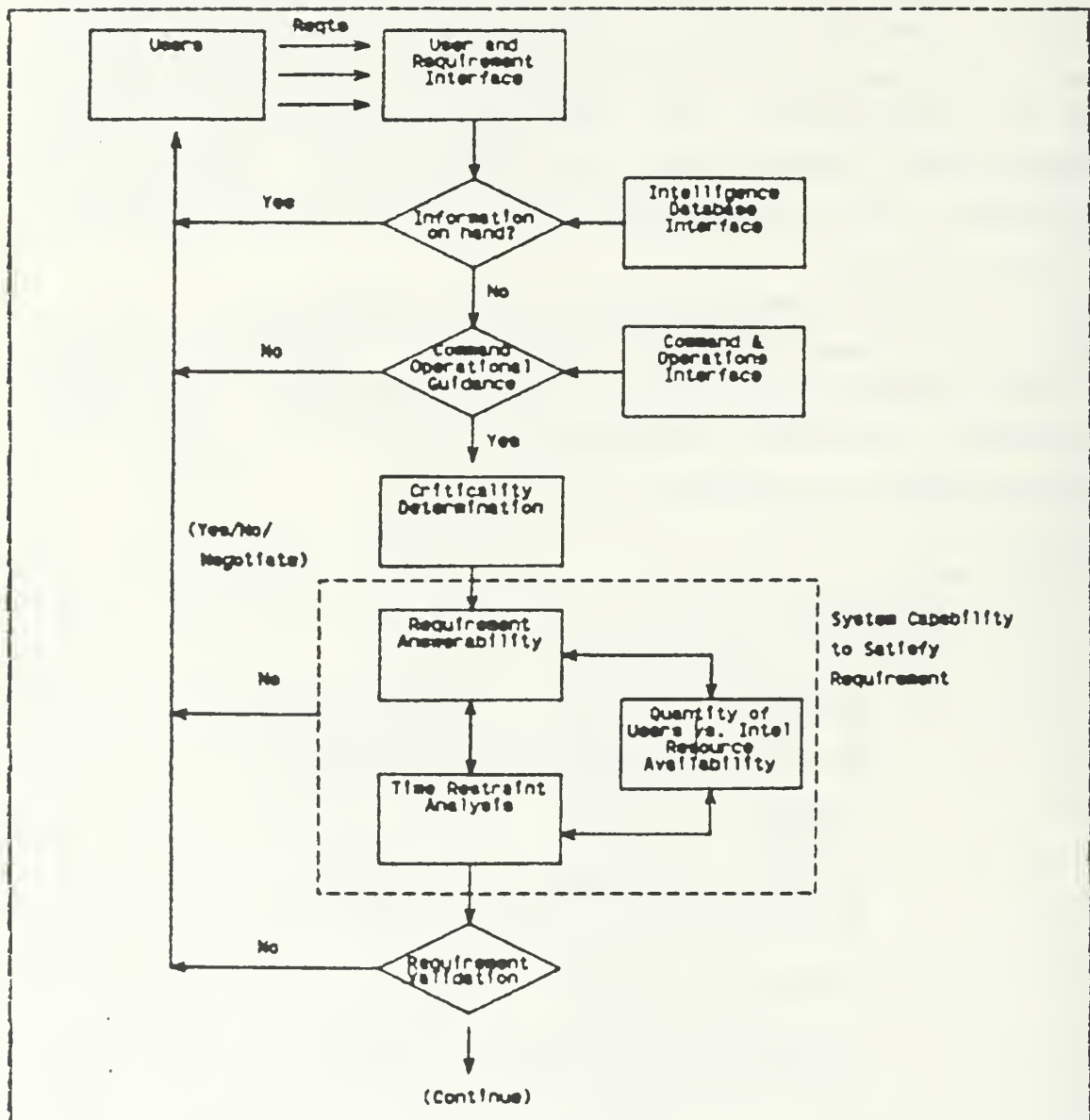


Figure 2.4 Requirements Filtering Process.

3. Detailed Requirements Analysis

After passing through the filtering process a requirement is considered to be valid - something which the intelligence system must react to (and hopefully satisfy). However, the functional structure of the intelligence system (requirements, analysis, collection) is fairly strict. Thus, the requirement must be further translated into functional terms which the system can act upon. The first step in this process is determining the dimensionality of the requirement. The dimensionality of a given intelligence requirement refers to whether or not that requirement can be satisfied using analytical intelligence resources, collection intelligence resources, or a combination of the two types of resources. Thus, a requirement can be thought of as being single dimensioned (either an analytical or collection requirement) or multi-dimensioned (an analytical and collection requirement). Figure 2.5 (Detailed Requirements Analysis) illustrates the dimensioning possibilities related to any given intelligence requirement.

Determination of the dimensionality of a given requirement may be a fairly complicated process. This is particularly true with respect to multi-dimensioned requirements. Such issues as resource availability and time become important factors which can create variability in the dimensionality of a requirement. For instance, given a rather vague requirement such as:

- Where will the enemy 2nd echelon be deployed?

One can envision the difficulty of determining which aspects of the requirement are analytical in nature and which are more collection oriented in nature.

It should be noted that once the dimensionality of a given requirement has been determined, it is not necessarily

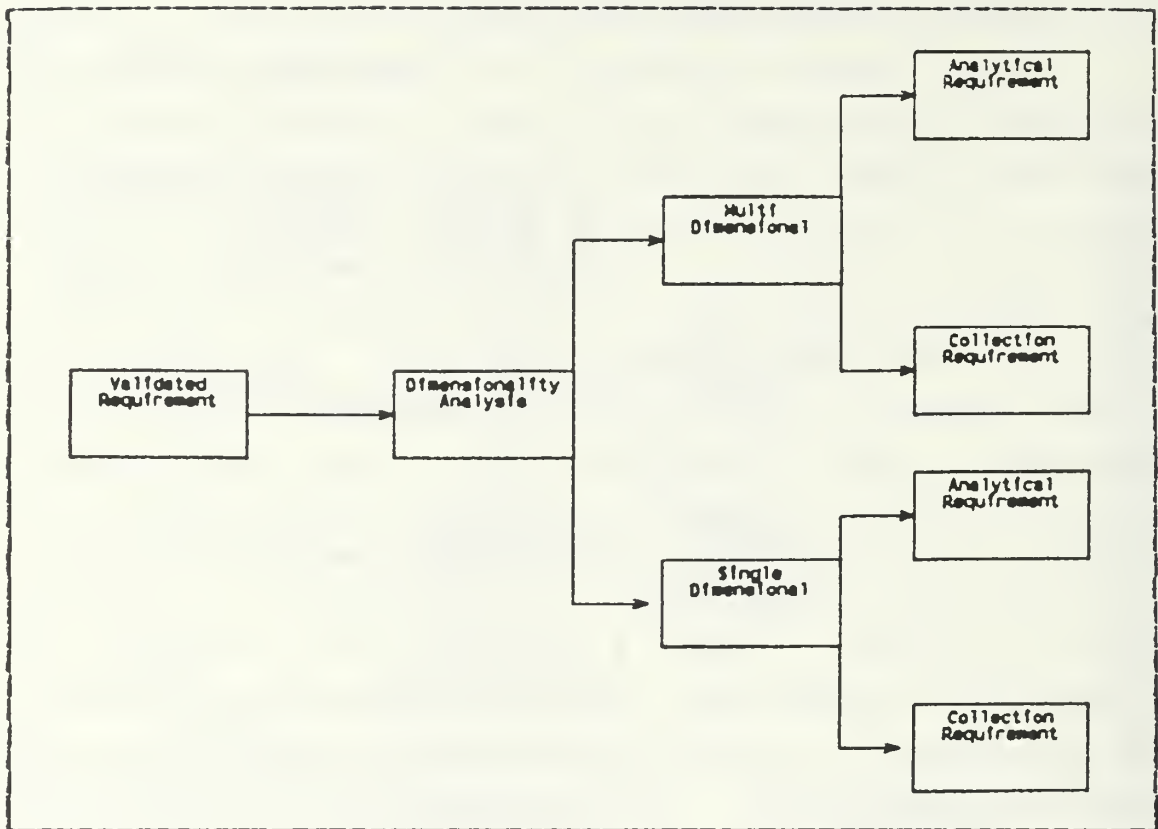


Figure 2.5 Detailed Requirements Analysis.

static. Specifically, the changing availability of analytical and collection resources affects the dimensionality of any given requirement. This fact suggests that some sort of interface should exist between the operational structures of the intelligence system with respect to valid intelligence requirements.

Once the dimensionality of a given intelligence requirement has been determined, it will be passed to the appropriate systems (analytical and/or collection). Each system will then continue to redefine the requirement into terms which relate to their own functions.

At this point in the process the requirements system has completed its function of receiving the requirement,

determining whether or not that requirement will be acted upon by the intelligence system, and forwarding a more functionally oriented requirement to either the analytical system, collection system, or both.

E. ANALYTICAL SYSTEM

1. Objective and Structure of the Analytical System

The objective of an analytical system is to piece together data from a variety of sources (to include judgmental) to provide the user with intelligence information of value. Given the intelligence system structure depicted in Figure 2.1 and the previous discussion concerning the intelligence requirements system, an analytical system might appear as that shown in Figure 2.6. Several features of this structure are noteworthy.

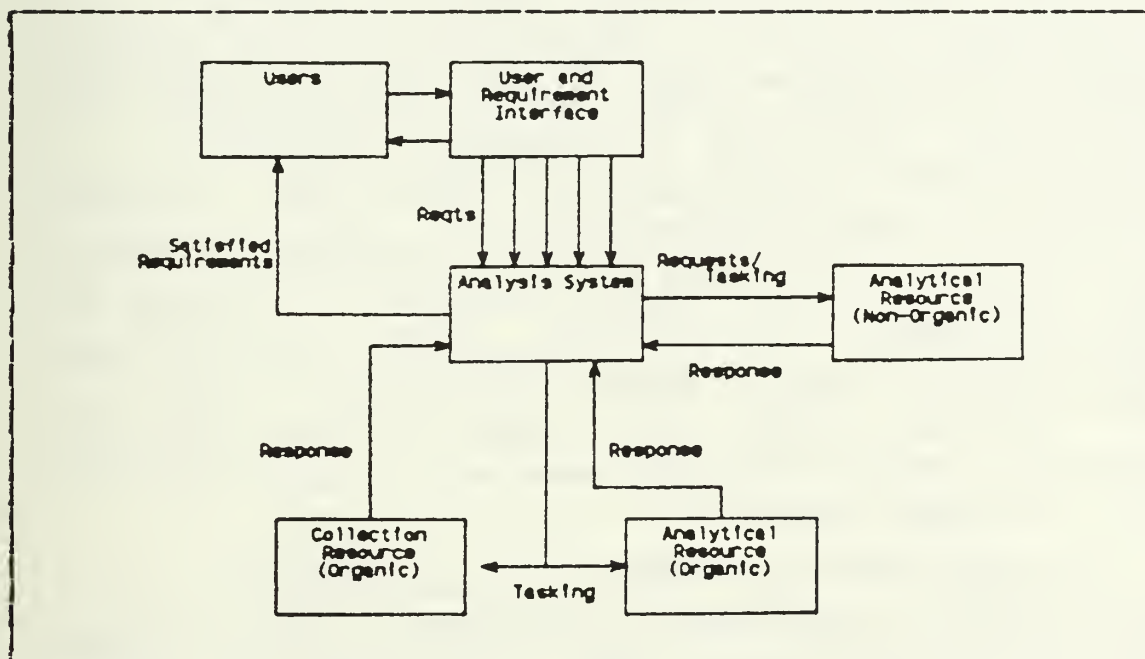


Figure 2.6 Analytical System.

a. Tasking of the Analytical System

The analysis system is tasked (within the intelligence systems structure) by the requirements system. This relationship implies that the analysis system must receive incoming valid requirements (described functionally as outlined in the previous section) and provide some level of feedback regarding the status of that requirement. The analysis system must also be able to task the collection system in order to help satisfy its informational shortfalls.

b. Non-organic Analytical Resources

A relationship exists between an analytical system and other non-organic analytical resources. Such resources might include analytical activities of subordinate, superior, or supporting units and organizations. This relationship could be defined in terms of authority (i.e. one organization would have tasking authority over another) or in terms of a liaison type function (which suggests only cooperative actions between the designated activities).

These two characteristics imply that the capabilities of an analytical system are not necessarily static and may change in structure during the course of a given combat operation. For instance, access to non-organic analytical assets may be limited if the unit is serving in a reserve capacity. Access would probably increase, however, in the event that the same unit were to be placed in direct contact with enemy forces.

Additional features of the analytical system make it difficult to describe. The nature of the analytical process is often subjective. This is primarily the result of the types of information the system is provided with and the types of information the system is asked to produce.

2. Time Considerations of the Analytical System

a. Analysis Under Conditions of Partial Information

Time restraints often require that analysis be performed with only a portion of the required information available. In this situation of partial information subjective judgements tend to bridge the gap between known information concerning the current situation and previously determined battlefield relationships. Analysis of this nature is risky in the sense that it is based upon a less than adequate informational foundation.

b. Analysis With Conflicting Information

Analysis often occurs under conditions of conflicting information. Information pertaining to an intelligence requirement will sometimes be of a contradictory nature. In this situation the analysis activity must be able to evaluate which information is best suited for inclusion in the analytical process. This evaluation can be complicated and time consuming in that questionable information of potential importance may be of such a complicated form that it must first be re-evaluated by the collecting activity. Subsequent time-lag complications often hinder the information evaluation process even further. The net result of these complications is that the decision as to which set of information is more accurate becomes judgemental and often less than objective in nature.

c. Time and Spatial Projection of Analyses

Intelligence analysis must be predictive in nature. Thus, the analysis activity must be able to (based on past information for the most part) project their analyses into the future to answer such questions as:

- When will the enemy be prepared to attack?

- When will the 2nd echelon arrive at the FLOT (Front Line of Troops)?

Additionally, the analysis activity must be able to project from a spatial point of view. For instance, analysis must address questions of the form:

- Where will the enemy be located in 6 hours?

Some of these predictive evaluations may be suited to mathematical models. Specifically, movement models and enemy arrival rate models may have a certain level of applicability. However, the information upon which models must depend may or may not be at a level of accuracy or precision which is required for satisfactory model performance.

For the reasons mentioned in the previous discussion it should be clear that modeling an analysis system would be a difficult task due to its subjective functional nature. Fortunately, this study is only concerned with the relationship between the collection system (the primary subject of this study) and the analytical system. Specifically, an analytical system tasks a collection system to help satisfy intelligence requirements.

III. A COLLECTION SYSTEM OVERVIEW

A. OBJECTIVE OF A COLLECTION SYSTEM

The objective of a collection system is to satisfy, in the context of the battlefield situation, informational shortfalls resulting from intelligence requirements being placed upon the intelligence system. A collection system accomplishes its objectives through the employment of a wide variety of sensors (both human and technical) which have the capability of detecting different forms of enemy activity. The employment of these sensors, however, is not necessarily direct. For the remainder of this study intelligence collection sensors will be referred to as collection platforms. Collection platforms can be highly specialized (discussed in more detail later). The operation of such platforms, accordingly, is often complicated and requires substantial personnel and support resources. These resources, to include their related collection platform(s), will be referred to as a collection subsystem. A collection system is composed of one or more collection subsystems (normally more). Thus, a collection system acquires needed intelligence information through the management of one or more collection subsystems.

B. STRUCTURE OF A COLLECTION SYSTEM

1. Collection Platforms

Collection platforms are sensors, both human and technical, which possess some capability of detecting certain forms of enemy activity or presence. Operationally deployed platforms are numerous in quantity and vary greatly

in their functional medium and operational capabilities. It is easy to distinguish and separately classify human platforms from technical platforms. Different types of technical platforms are more difficult to classify. Normally they are categorized into groups according to the manner in which intelligence information is collected. For instance, those which collect signal related intelligence information are grouped into a functional category referred to as SIGINT (standing for signal intelligence) platforms. Similarly, those technical platforms which employ images in the collection process are grouped into a functional category referred to as IMINT (standing for imagery intelligence) platforms. For obvious reasons, human intelligence sensors are referred to functionally as HUMINT platforms.

As previously mentioned, collection platforms are useful because they possess a valuable operational capability. This capability can be defined as a function of the following parameters:

a. Functional Medium (M_f)

For human platforms the medium is obvious. Technical platforms tend to operate (collect information) at some location (or within some range) of the electromagnetic spectrum. For instance, communications intercept platforms normally collect information over some range of frequencies (and transmission modes) - HF, microwave, etc. Similarly, photographic platforms collect over some range of light frequencies - IR, visual, etc.

b. Functional Capability (C_f)

Given the medium in which a platform operates it must also possess some limits to its sensing capabilities. Those limits might be resolution levels, sensitivity levels, maximum/minimum range capabilities, etc.

c. Physical Medium (M_D)

For the Air/Land battle we are obviously concerned whether the platform operates on the ground, in the air, or both.

d. Physical Capability (C_D)

This parameter refers to the limits on the physical capabilities of the platform. These limits would perhaps would identify the platform as having a night or all-weather capability vs. a strictly daylight capability.

e. Time (T)

Time is an extremely important parameter. Although a strong argument could be made that time is related to either the functional or physical capability of a given platform, it is identified separately because of its critical importance. There are several reasons the time parameter receives such distinction. First, a given collection platform may need a certain amount of time to perform its collection function. For instance, a aerial surveillance radar may require a particular amount of emission time in order to collect an image of its area of concern on the battlefield. Second, time may be required to satisfy the physical limitations of the platform. In particular, an aerial platform may have to fly from a distant airfield to its collection point (and return) - thus consuming time. Numerous additional time related factors could potentially affect the operation of a given collection platform (atmospheric conditions at night in Europe tend to disrupt certain forms of HF communications systems) and thus time is presented as a separate parameter defining the operational capability of a collection platform.

The operational capability (O.C.) of a collection platform can be represented by the following relationship:

$$OC = f(M_f, C_f, M_p, C_p, T) \quad (\text{eqn 3.1})$$

2. Collection Subsystems

A collection subsystem consists of those resources, both human and technical, which directly control the operational employment of a collection platform. One or more collection platforms may be under the control of a collection subsystem at any given time during an operation. Collection platforms, when under the control of a collection subsystem, are considered part of the collection subsystem.

Collection subsystems normally control platforms which are functionally related to one another. For instance, a signal intelligence collection subsystem would normally control collection platforms which are capable of detecting and perhaps analyzing enemy communications and non-communications emitters. Likewise, an imagery intelligence collection subsystem would normally consist of all collection platforms which, in the process of collecting information on the enemy, produce images for analysis. On occasion, collection subsystems are organized along less functional lines. For instance, there exist both Army and Air Force collection platforms which produce radar images of potential battlefields. Although the platforms are functionally similar they are not normally found under the control of a single collection subsystem. Each service tends to control its own platforms. Thus, in this

situation, functionally similar collection platforms are controlled by separate service related collection subsystems.

It seems reasonable to suggest that the operational capability of a given collection subsystem might be expressed as the sum of the operational capabilities of its collection platforms. This relationship might be valid if it could be shown that the parameters of each platform were independent of one another. Unfortunately, this is not true in all cases.

a. Functional Medium

In the event the collection platforms operate in entirely different portions of the electromagnetic spectrum then one could reasonably argue for independence with respect to this parameter and a simple subsystem parameter could be formulated. Otherwise, some relationship between platforms would exist and the formulation of a subsystem parameter would be more difficult.

b. Functional Capability

In the event that the functional medium of the platforms of concern were determined to be independent then it is likely that their functional capability parameters would also be independent of one another. If their respective M_f s were dependent, however, then there would be a possibility that they would also be dependent with respect to the capability parameter.

c. Physical Medium

In the event that two or more collection platforms required an identical portion of a physical medium in which to operate then a dependent relationship with respect to this parameter would exist. At first glance, the

possibility of the occurrence of this problem might seem remote. Consider, however, the availability of communications advantageous terrain on a potential battlefield. The availability of such terrain can and often is quite limited and thus the possibility that two or more platforms would compete for the use of such terrain appears more likely. Thus, if two or more platforms have a common physical medium the possibility exists for a dependent relationship and a subsystem representation of this relationship would have to be developed.

d. Physical Capability

If the physical mediums of collection platforms are dependent upon one another then the possibility exists that the capability parameter of those systems are also dependent. This situation is similar to that between functional medium and functional capability described in Paragraph (k) above.

e. Time

It is likely that the time parameter of an individual platform is related to that of another if any of their other parameters are related. Thus, the probability of a relationship between the time parameters of two or more collection platforms is greater than that of any other single parameter.

A simple algorithm which could help determine the existence of parameter dependencies among the collection platforms of a collection subsystem is outlined at Figure 3.1.

It is clear that dependencies between operational parameters of a given set of collection platforms could be identified. The interpretation of such dependencies is, however, more difficult if not impossible to

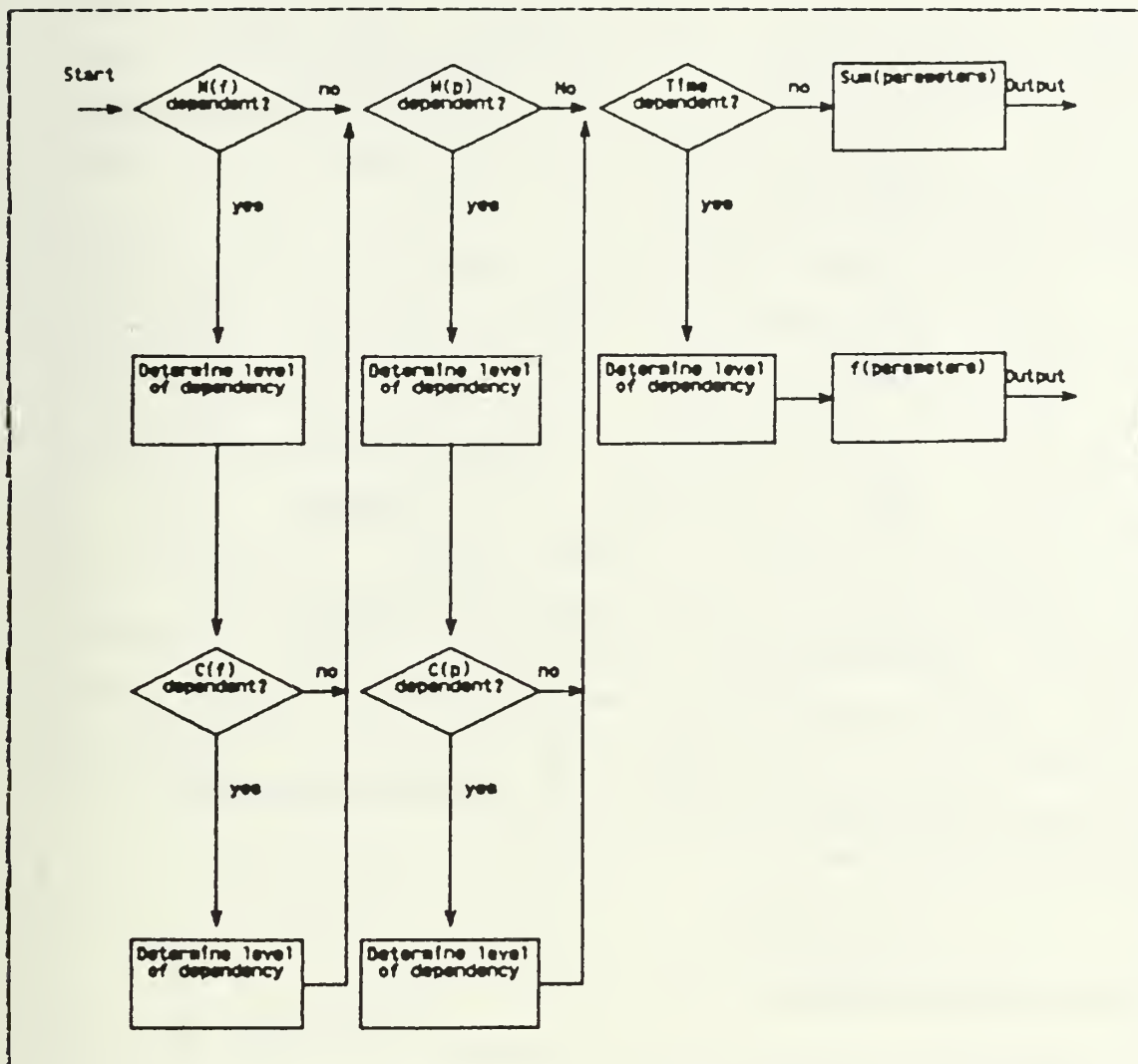


Figure 3.1 Dependency Analysis.

determine. Thus, the suggestion to represent the operational capability of a given collection subsystem as a simple sum of the operational capabilities of its collection platforms is not justified except in cases where no dependencies exist.

Further investigations in determining these sorts of relationships would certainly be appropriate. For the purposes of this project, it will be assumed that a

composite relationship representing the operational parameters of a group of collection platforms can be formulated. From this composite relationship a representation of the operational capability of a given collection subsystem could be formulated.

Recall that collection subsystems often consist of collection platforms with similar functional capabilities. For this reason one could think of a given collection subsystem as an entity which would be associated with collecting a certain class or category of intelligence information. The categories of information which a subsystem would be able to collect would, of course, be quite closely related to the operational capabilities of the subsystem. The operational capability of a given subsystem, in turn, would be defined by the relationship between platform capabilities (discussed above) and any efficiency or inefficiency multipliers associated with the management of a collection subsystem.

C. COLLECTION SYSTEM

A collection system consists of one or more collection subsystems and all the resources necessary for its (their) control. A collection system consisting of nine collection platforms and three collection subsystems could be structured in a variety of manners. Two possible structures are depicted on Figure 3.2.

The exact structure of a given collection system is determined by the quantity and type of subsystems and platforms under its control. During an operation the number of subsystems under a unit's control will change as a function of battlefield relationships. Thus, the structure of a collection system is itself, a variable. This is an

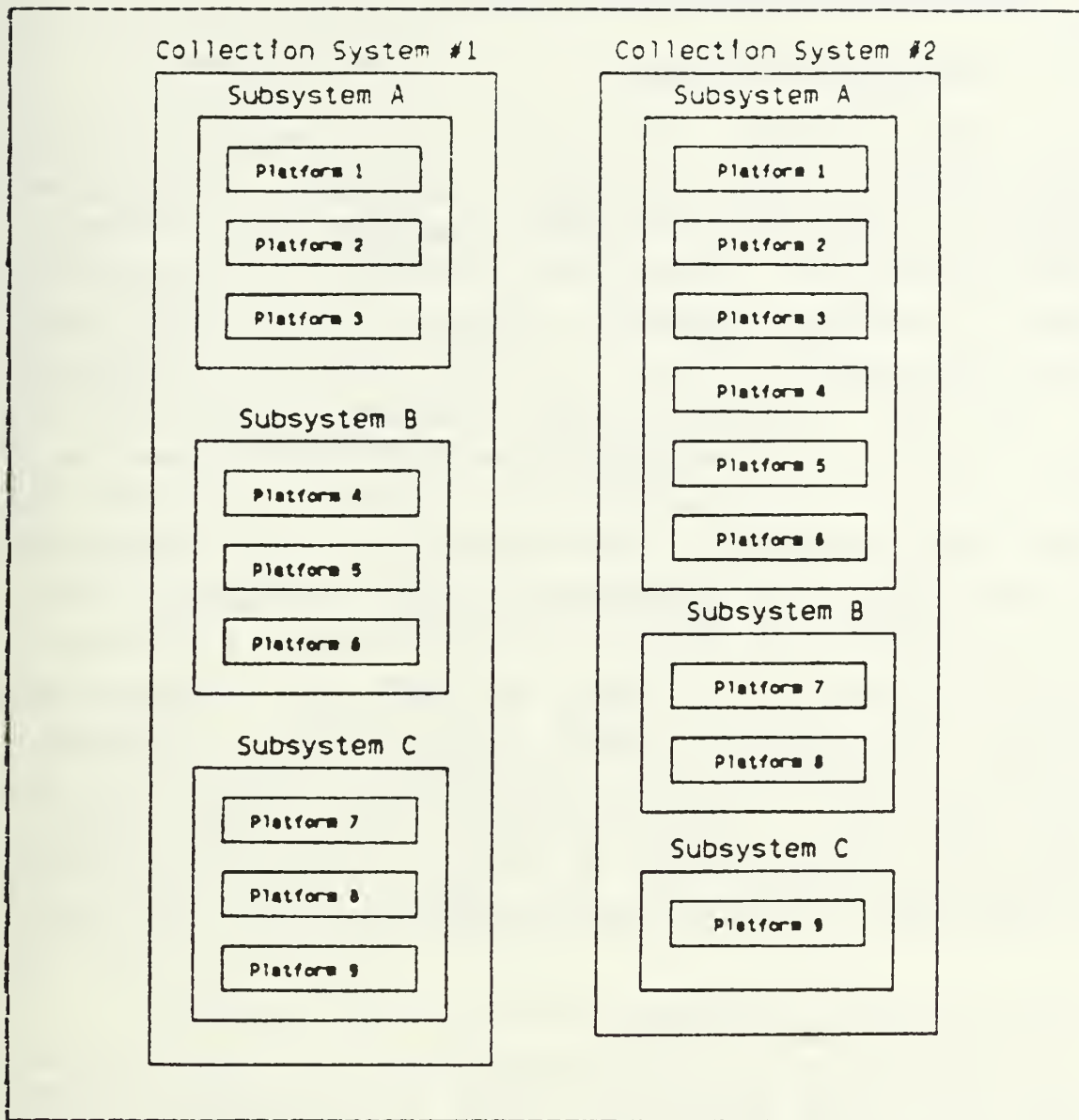


Figure 3.2 Collection Systems Structures.

important concept. The implication being that as the course of the battle changes, the structure (and hence capability) of the intelligence collection system will also change.

The next portion of the study will address the functions of the various components of the collection system structure.

D. FUNCTIONS OF A CCILECTION SYSTEM

1. Collection Platforms

The collection platform is the fundamental unit and scarce resource of the ccollection system. The entire collection system and subsystems were developed to effectively cntrol the collection platform. As objects of control collection platforms receive inputs from their controlling source, respond to these inputs by interfacing in some form or another with measureable indications of enemy activity, and return (to the controller) operational data related to that interfacing activity. In order to successfully accomplish these functions a given collection platform must be able to communicate (input and output) with its cntrollers. A diagram of the functions a collection platform must perform is shown at Figure 3.3. Many variations of this functional model are possible. One ccommon variation occurs when the collection platform sends raw operational data to activities cther than the controllers. Otherwise, the model shown at Figure 3.3 is general enough to cover many of the platforms currently in use by the Army.

2. Collection Subsystems

Collection subsystems control the operation of one or more collection platforms. As a controlling source they must provide control input which is understandable to each platform within the subsystem. From each platform the collection subsystem receives intelligence data.

Collection subsystems are also controlled by collection systems. As a controlled system it must receive control inputs from its controlling source and provide intelligence data (perhaps translated) to the controlling source. The control inputs from the collection system to

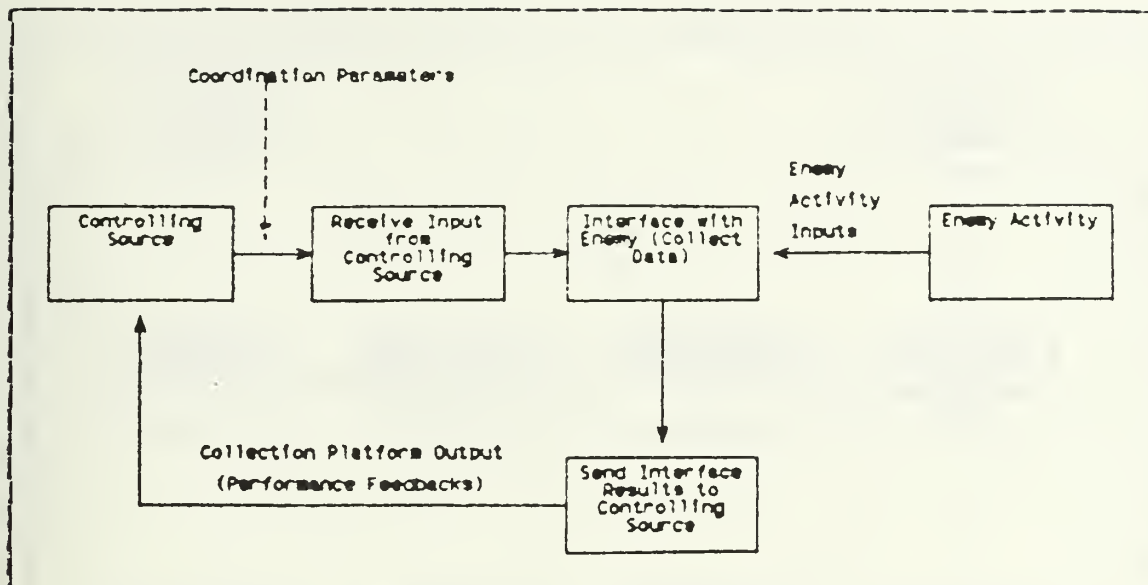


Figure 3.3 Collection Platform Functions.

the subsystem will not be identical to those from the subsystem to the platform. They (subsystem to platform inputs) will for the most part, however, reflect the intentions of the system to subsystem inputs. Likewise, the intelligence data received from the platform may not be identical to that forwarded from the collection subsystem to the collection system.

Technical and specialized platforms require precise control inputs and return precise data - neither of which is normally comprehensible to the untrained user. Thus the requirement for the subsystem to serve as a translator. As the number of collection platforms increase in a given collection subsystem one can easily see how the functional complexity of the subsystem increases. This is particularly true in the case of widely varying types of collection platforms. Figure 3.4 depicts the functions of a collection subsystem.

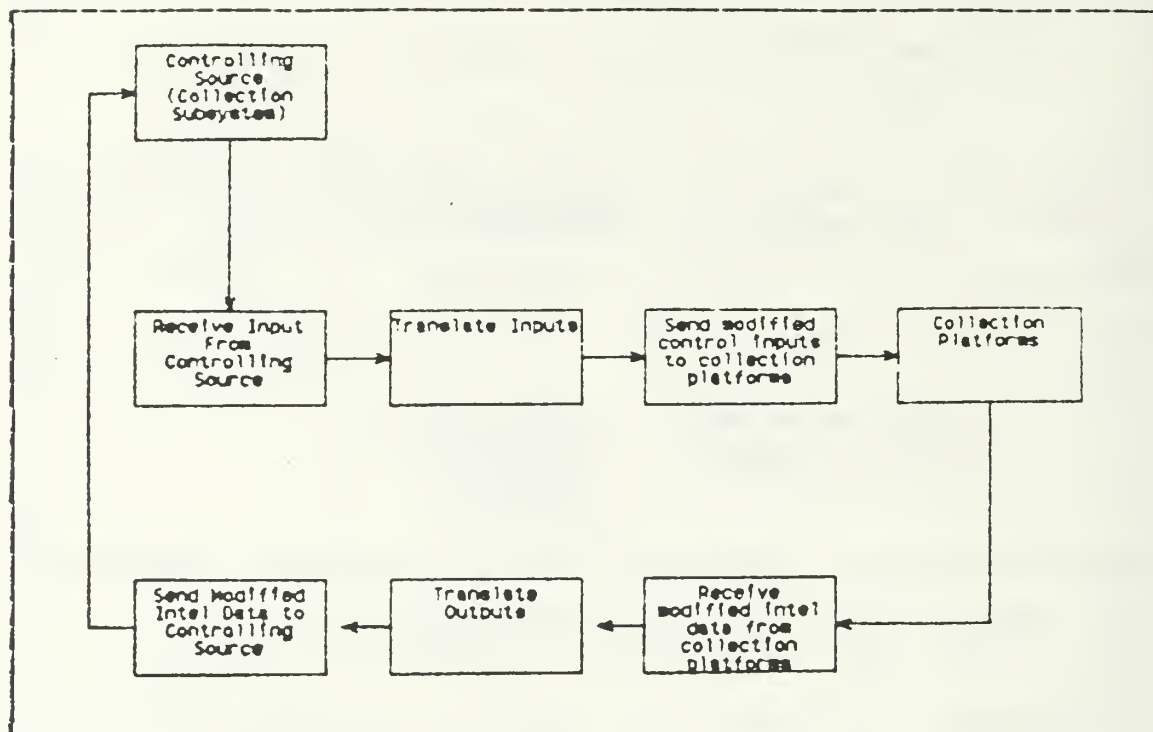


Figure 3.4 Collection Subsystem Functions.

3. Collection Systems

Collection systems control the operations of one or more collection subsystems. To accomplish this task the collection system forwards controlling inputs to appropriate subsystems and receives intelligence data from them (or on occasion directly from a collection platform). The collection system is also controlled (as previously mentioned) by other elements within the intelligence system (analytical and collection systems). A collection system is functionally similar to the general collection subsystem shown in Figure 3.4. In this case, however, the controlling sources are elements of the intelligence system and the platforms are collection subsystems. Figure 3.5 depicts the functional nature of a collection system.

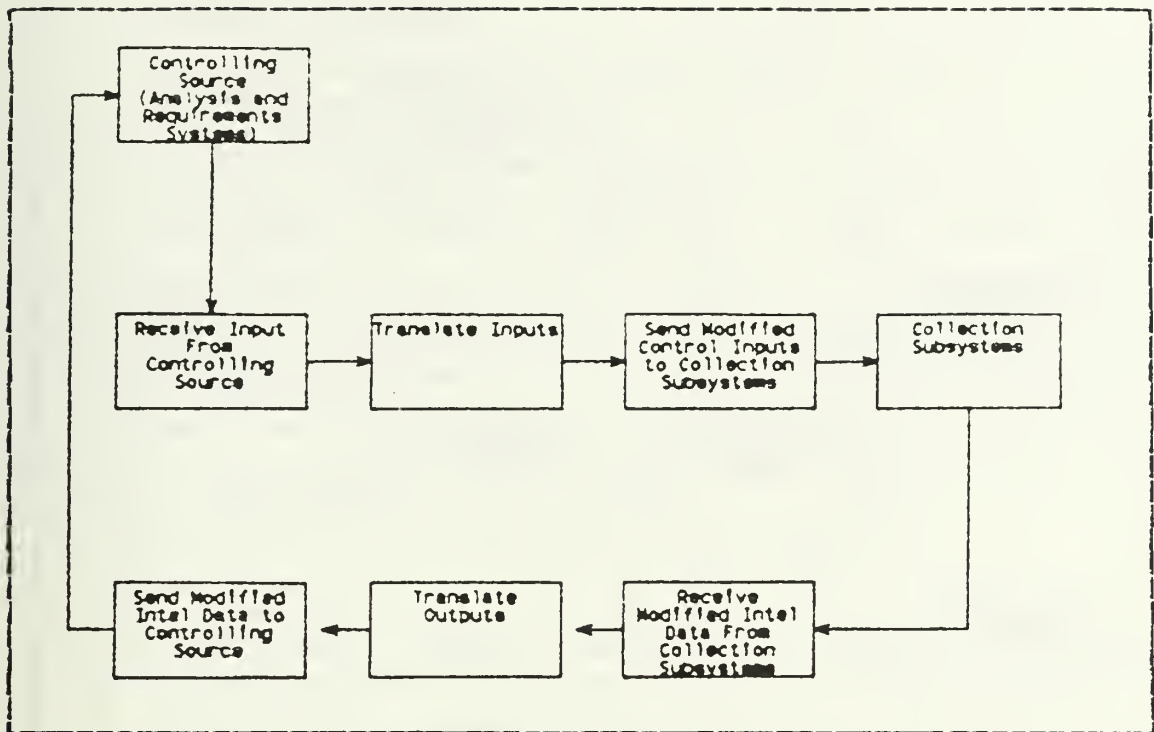


Figure 3.5 Collection System Functions.

E. GENERAL CONSIDERATIONS OF A COLLECTION SYSTEM

Given the intelligence system structure outlined in Chapter Two and the discussion in this chapter it is now possible to illustrate, in more precise detail, how a collection system fits into that structure. The system at Figure 3.6 is a multilevel depiction of the intelligence system with the strata being the collection platforms, subsystems, collection system, and finally the intelligence system.

1. Multiple Collection Platforms and Subsystems

Complexity increases as more collection platforms (and subsystems) are added to the intelligence collection system. More resources are required to manage the

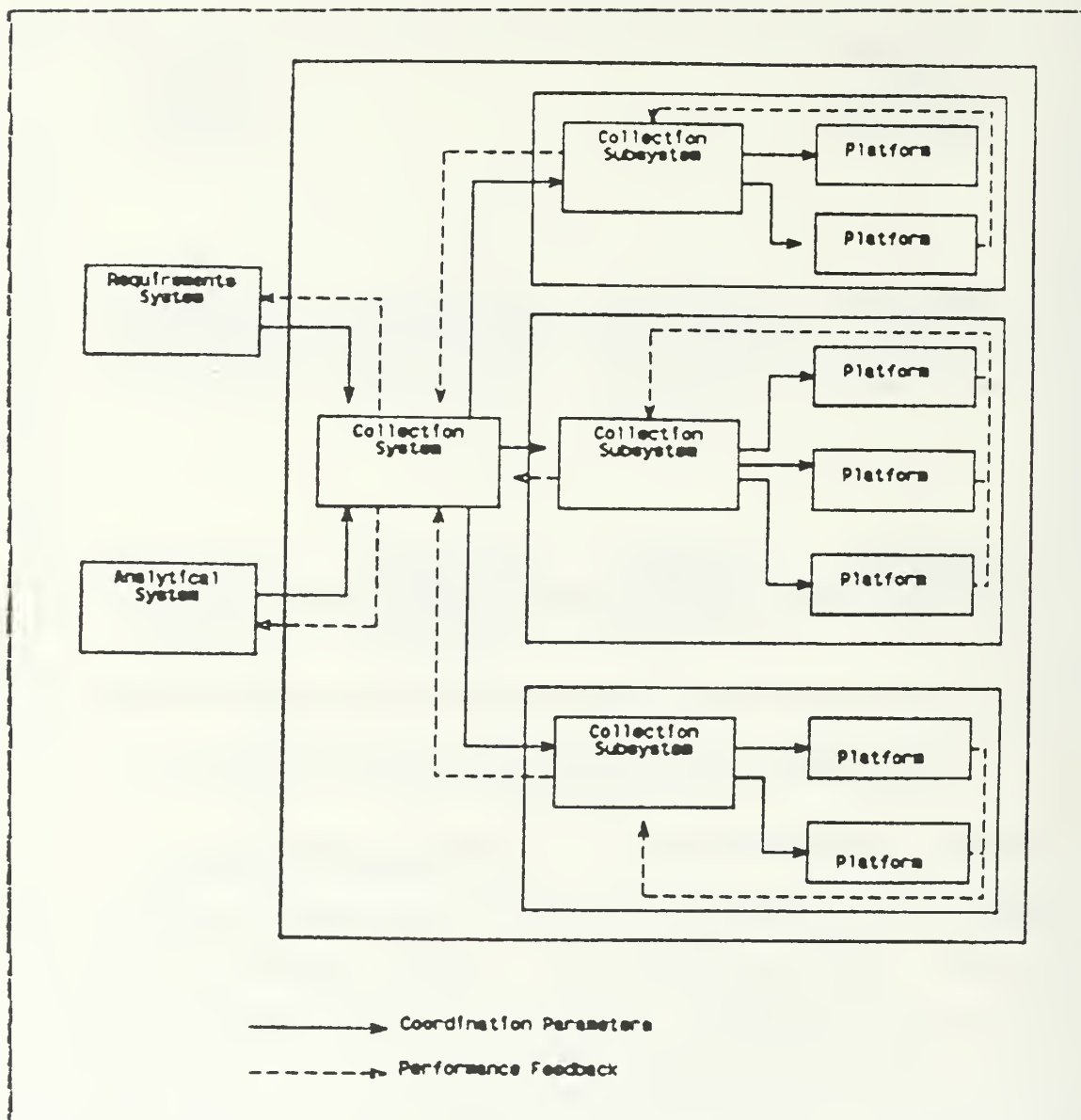


Figure 3.6 Collection System Overview.

collection effort of the platforms (using subsystems as intermediate controlling sources) and also to manage the increased data flow from the platforms into the collection system.

2. Dynamic Structure

Changing battlefield conditions often dictate changes in military organizational structures. As alluded to in previous discussion, collection systems experience such battlefield structural changes. These changes are often more abrupt (occur without warning) than those found in more typical military units. This is the result of the multiservice/multicommand make-up of collection platforms and subsystems. This dynamic structure adds complexity to both the management of the collection effort and the resulting data flow.

3. Time and Spatial Projection of Intelligence Collection

The intelligence collection system, for the most part, responds to the needs of the the Requirement and Analytical Systems of the Generalized Intelligence System. These needs invariably are more concerned about the future nature of the enemy on the battlefield rather than their current status. As a result, the collection effort must also be focused on the future. This orientation adds complexity in planning and implementing intelligence collection operations. Lead/lag time considerations for both platform performance and the many levels of planning required is a difficult problem in itself. Much effort is currently aimed at solving scheduling problems arising from lead/lag time considerations. Added to these time difficulties is the spatially dynamic nature of the battlefield. The location of the enemy forces of concern at unknown future times is difficult to determine. Thus the future orientation of the intelligence system tends to create planning and implementation difficulties for the collection system.

4. Multiple Users with Different and Changing Levels of Access

Numerous users are allowed access to the resources of a collection system. The mere variety associated with such numbers implies that a collection system's capabilities (with respect to both the collection effort and transmission of information) must be broad. Increased quantities of users leads to obvious difficulties in managing any complex system. Users of a collection system are, with the aid of a priority system, allowed varying degrees of access. A high priority unit would normally be allowed greater access than a low priority unit. The priority of access often changes during the course of an operation as units are shifted about the battlefield. The collection system should be able to cope with such changes.

These and other considerations suggest that a description of the structure and functions of a collection system might be somewhat complicated. The collection system is not the master of its own destiny. The number of users (and their level of access) as well as the number of resources needed to satisfy those users both vary as a function of current battlefield conditions.

IV. COLLECTION REQUIREMENTS

The control parameters of collection systems, subsystems, and platforms are intelligence collection requirements or translated portions of intelligence collection requirements. To understand the nature of the collection system one must understand collection requirements. This chapter will address the traditional perspective of collection requirements, describe their flow through a collection system, and suggest a more analytical view of a collection requirement.

A. SOURCES AND TYPES OF COLLECTION REQUIREMENTS

A collection requirement is leveled against a collection system as a result of an informational need identified by the user. All users in this systems structure can be thought of as members of one of the three sub-elements of the Generalized Intelligence System. Therefore, collection requirements can enter a collection system from one of the following three sources:

1. Requirements System

Collection requirements originating from a requirements system are those which have been initially identified as requiring some degree of intelligence collection effort prior to being satisfied. An example of such a requirement might be:

- Determine if enemy tanks are located at coordinates ABxxxxxx.

An intelligence database could address the question of whether or not tanks were located at those coordinates at

some point in time in the past. Collection at that location in near real time, however, must be accomplished in order to answer the requirement as stated.

2. Analytical System

Collection requirements can originate from an analysis system in two primary fashions. The initial evaluation of the intelligence requirement by the requirements system as primarily analytical in nature (its dimensionality) could have been, to some degree or another, incorrect. An analysis system would, in this situation, not have the assets available to satisfy such an ill-assigned requirement and would be forced to pass the requirement onto the collection system for satisfaction. An example of such a requirement might be:

- Notify the 3rd Brigade if there is an increase in moving target activity in their sector.

This requirement is clearly oriented toward a surveillance (and hence collection) activity. An analysis system would not normally have under its operational control such a surveillance capability and thus would be unable to effectively respond to the requirement.

The initial intelligence requirement may have been primarily analytical in nature but may have required additional collected information to enhance or upgrade the quality of analysis. An example of this type of requirement is:

- Determine the capability of the enemy force located at coordinates ABxxxxxx.

This is clearly an analytical requirement yet accurate collection (to determine the type and size of the enemy force) must be accomplished in order to more accurately perform the analysis.

The differences in both of these cases described above are really a matter of degree. The first case alludes to the possibility that a mistake in the assignment of requirements may have been made. The second case concerns those times when more information is needed to satisfy a given requirement.

3. Collection System

A collection system will, in order to maintain itself, generate collection requirements. These are the overhead costs of the collection subsystems. An example of such a requirement is:

- Determine radio frequencies the enemy is using to control its nuclear capable artillery.

In this case the radio frequencies are, in themselves, of little intelligence value to the user. However, they are vital to the SIGINT collection subsystem which is tasked with providing other forms of intelligence concerning such enemy forces.

In order to speed up the requirements and collection processes special types of collection requirements have been developed. The most common of these are listed below:

a. Standing Requirements

Standing requirements are those which a collection system is nearly always attempting to satisfy. Normally, standing requirements are applied to informational shortfalls of obvious importance.

- Enemy nuclear activity.
- Significant enemy movement on the battlefield.
- The location of enemy command posts.

The Army has traditionally referred to these sorts of requirements as EEI/CIR standing for Essential Elements of Information and Other Intelligence Requirements.

b. Fast-Track Requirements

Fast-Track Requirements. Fast-track requirements are those which, because of their time sensitive nature, are allowed to by-pass normal collection procedures.

- Verification of the location of an artillery target.
- Determination of target status for nuclear target planning.
- Any hot requirement of importance.

c. Dedicated Resources

Often portions of or an entire collection system (or subsystem) will be allocated for use by a single user. When this occurs the collection system becomes a dedicated resource. An example of this type of allocation might be when six reconnaissance sorties (out of a total of 20 available) are dedicated for use by a single maneuver brigade. No other users would be able to place intelligence requirements on those six sorties which might detract from their support of the maneuver brigade to which they are dedicated. The types of collection requirements described above will in this study be referred to as special requirements.

B. TRADITIONAL REQUIREMENTS FLOW

The requirements flow into any given type of collection system (supporting a collection subsystem or group of collection platforms) can be depicted as shown in figure 4.1. Some points should be noted when viewing this figure.

Special variations of collection requirements initiated in a requirements and analytical system are shown as inputs into special requirements. This is not meant to indicate that special requirements not related to those systems cannot exist independently. A dedicated resource requirement is an example of such an independent special requirement. Additionally, a collection system requirement can be thought of as totally enclosed within the collection system. Its primary function is to support collection platform and system operations although intelligence information generated from its application would, of course, not be ignored.

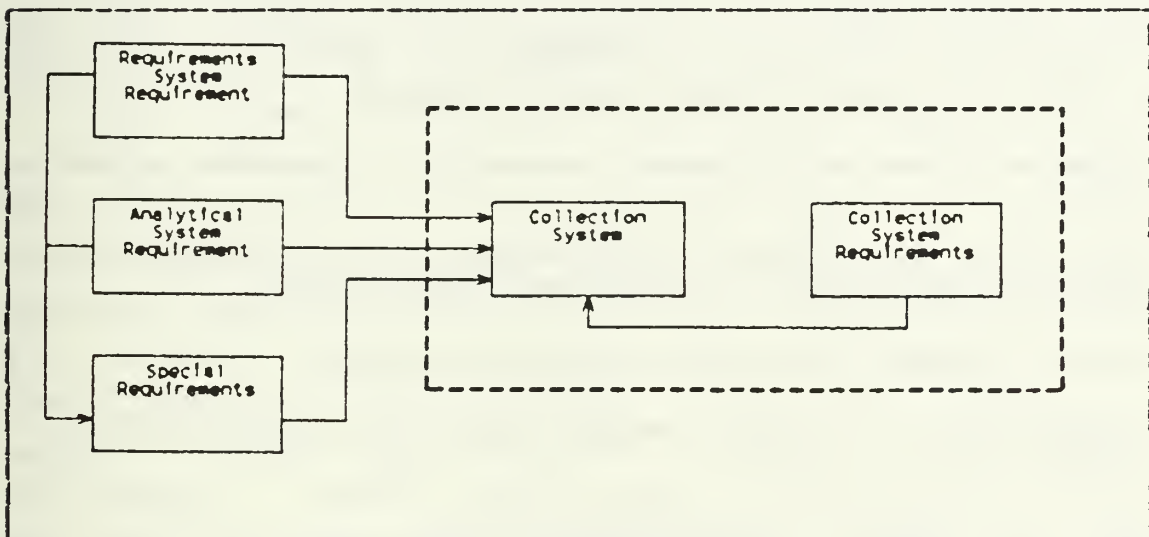


Figure 4.1 Requirements Flow.

The following discussion addresses the nature of the collection requirement as it relates to collection subsystems and their related collection platforms. For illustrative purposes the first portion of this discussion will address the relationship of a single collection requirement as it enters a single collection subsystem with its related platform(s). An example of such a collection subsystem

might be the Aerial Reconnaissance Subsystem containing such platforms as SLR and various other photographic sensors.

Traditionally, a collection requirement is forwarded, for the most part, to a collection subsystem in its entirety. The operators of the particular subsystem and platforms would then determine how the collection platforms under their management might be able to satisfy the given requirement. Occasionally, a collection requirement might be well suited to satisfaction by a particular subsystem and platform. On other occasions there may be little applicability.

This approach toward the management of intelligence requirements came about through an evolutionary process. Factors which shaped this process (and which will not be thoroughly addressed in this paper) include:

- The technical orientation of specific collection platforms.
- Security procedures (compartmentation) related to specific collection platforms and subsystems.
- Multi-service use of collection platforms.
- The limited data processing capabilities of battle-field users.
- Limited communications capabilities.

There are advantages and disadvantages associated with this platform oriented approach toward collection management. The operators of each specific collection subsystem are aware of the intent of the collection requirement and are thus better able to operate their subsystem to satisfy that intent. Given the technical nature of a specific collection subsystem, an argument can be made that the operators of that subsystem are best capable of determining which portions of a given intelligence collection requirement can be satisfied by their subsystem and its related platforms.

Disadvantages to this system become apparent when looking at a group of collection subsystems operating under a single system. This is the more realistic situation. A glimpse of the potential complexity of such a system can be seen at Figure 4.2. Some of the specific disadvantages include the possibility for the occurrence of uncontrolled redundancy of effort and the possibility that one or more collection subsystems can become saturated with collection requirements while others operate at less than optimal levels of efficiency. This type of control problem can become important when one considers the fact that intelligence information is generally of a time sensitive nature and hence delays in satisfaction of a requirement will degrade the value of the information required by the user.

In an attempt to provide some sort of administrative control and traceability of the great quantities of collection requirements in the collection system a collation process has evolved. The exact structure and manner in which this process works is ad hoc and varies greatly from unit to unit. Some processes are more efficient than others. All of these processes do have some features in common. First, they attempt to filter out unsuitable requirements. Second, they attempt to keep track of which users have submitted which requirements. Finally, they attempt to get appropriate requirements to those collection subsystems which may be able to satisfy them.

Once collection subsystems have responded to a collection requirement (through platform collection or perhaps a negative response) then a sort of reverse collation process - dubbed Collection Fusion - takes place. Similar to the initial collation process described above, one goal of this process is to match information/intelligence data to the users that requested it. Great efforts and achievement have been made in recent years in the area of collection and

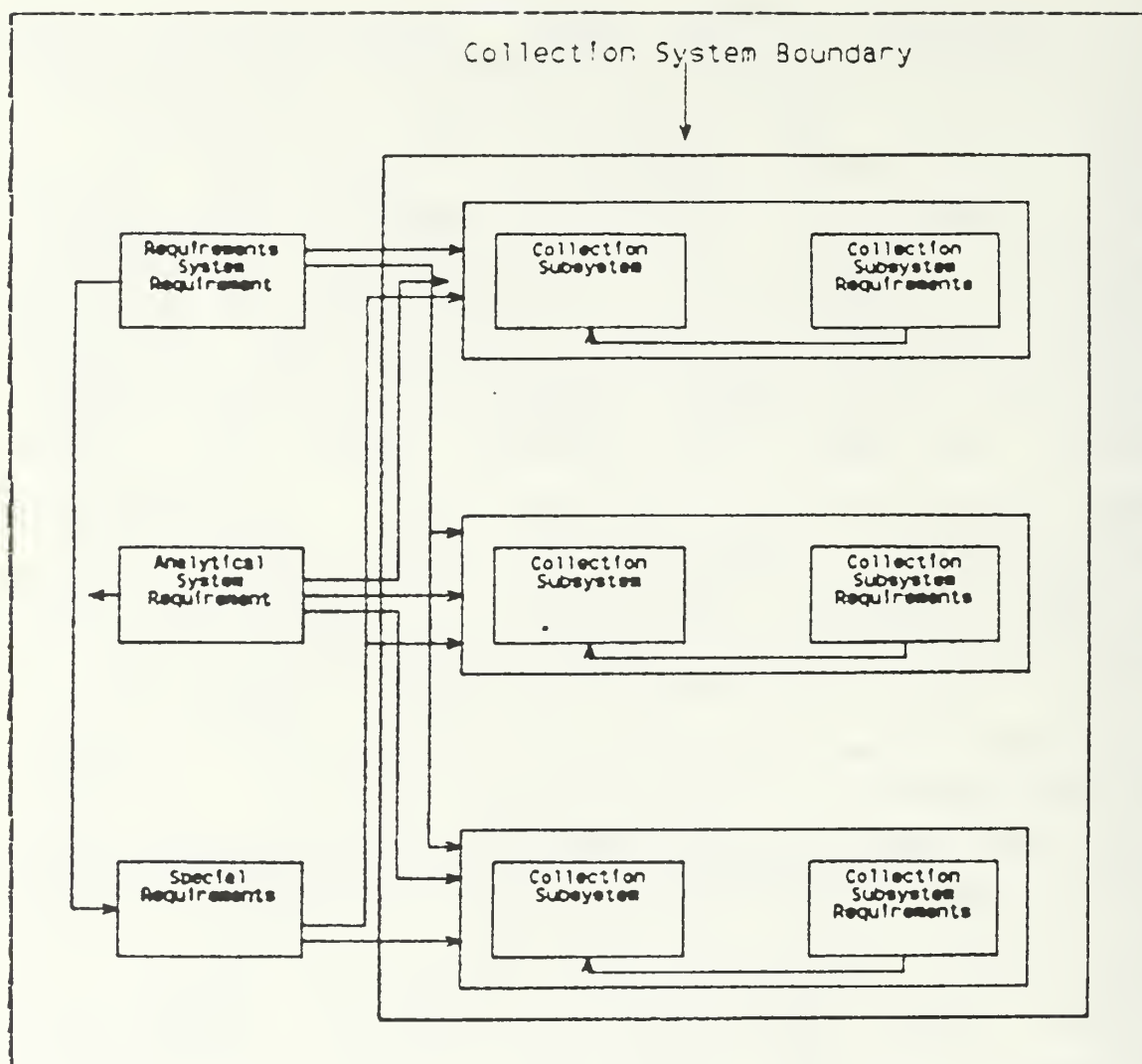


Figure 4.2 Composite Collection System.

intelligence fusion. For this reason, the topic of collection fusion will not be addressed in detail in the remainder of the study.

Thus, most collection systems deployed by major units today are similar in structure to that shown in Figure 4.3. Prior to investigating methods which could improve the collection management process outlined in this chapter it is first necessary to examine, in more analytical detail, the nature of a collection requirement.

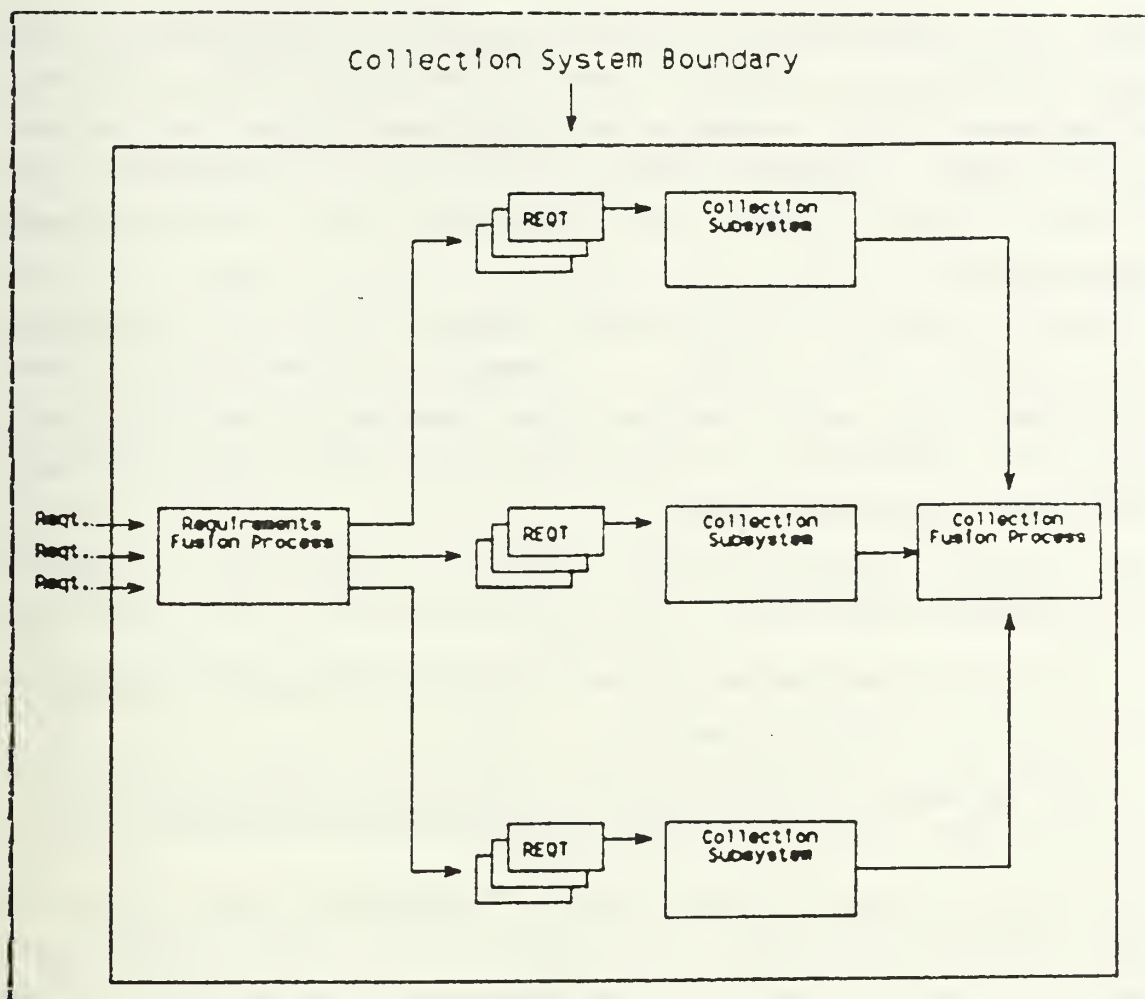


Figure 4.3 Traditional Collection Management Approach.

C. DECOMPOSITION OF A COLLECTION REQUIREMENT

Collection requirements entering a collection system are, in general, not in a form which collection subsystems and platforms can immediately use. Normally the requirement must first be re-expressed into more familiar terms which have a more direct relationship to those tasks which subsystems and platforms perform. This re-expression process tends to narrow the scope of the original collection requirement into more manageable portions. Collection

subsystems subjectively accomplish this re-expression in many collection systems found in use today. The re-expression of a collection requirement into a set of smaller, more manageable subrequirements will be referred to in this study as the decomposition of a collection requirement.

Upon receipt of a collection requirement a given collection subsystem will attempt to interpret the meaning of that requirement in terms of its own subsystem and related collection platforms. For example, given an incoming collection requirement of:

- Determine if the enemy forces located at X are preparing to attack.

An aerial reconnaissance collection subsystem might generate the following subrequirements:

- Take an aerial photograph of location X to determine if the enemy located there is in an attack posture.*
- Provide moving target radar coverage of area X to determine if the enemy is moving toward friendly lines.

Given the same collection requirement a signal intelligence collection subsystem might generate the following subrequirement:

- Intercept the radio communications of enemy units located at X to determine if they are preparing to attack.

It is possible (and in practice often occurs) that a collection subsystem might not be suited to such a collection operation and would not be able to generate any feasible collection subrequirements.

Note that in the examples provided above that the generated subrequirements have been re-expressed with respect to the capabilities of the collection subsystem. Also, although each subrequirement appears to be directed toward a

single collection platform, this may not be the case. For instance, it is possible that several subrequirements derived from a single collection requirement may be directed toward the same collection platform. Finally, each of the subrequirements in the example are basically qualitative in nature. They capture the nature and intent of the original requirement without dealing with any of the more specific parameters of the requirement.

Taking this decomposition process one step further, consider first the subrequirement of the aerial reconnaissance collection subsystem (labelled with an asterisk above). An aerial photographic collection platform may decompose that subrequirement in the following manner:

- Provide black and white, low panoramic and vertical, photographs of location X.
- Provide black and white, low panoramic and vertical, photographs of major roads leading from location X to the nearest friendly forces.

Although these subrequirements are certainly very detailed (when compared to those of the collection subsystem), they still are oriented toward the satisfaction of the nature and intent of the original collection requirement.

The subrequirements addressed in the preceding paragraphs will be labelled as quality subrequirements. Any given collection requirement will also have associated with it another set of parameters which are more technical in nature. The primary example of such a technical parameter is the time restraint associated with a given subrequirement.

Time restraints were mentioned briefly in Chapter One as they pertained to general intelligence requirements. Many of the same concepts apply with respect to the decomposition of collection requirements except in a much more detailed fashion. A collection requirement enters the collection system with at least two time restraints associated with it.

- The time by which the user must have the desired information. This restraint tells the collection system when the collected intelligence must be in the user's hands. Commonly used terms describing this restraint are "best possible" or "as soon as possible" (both of which provide some degree of system flexibility) and "not later than/not earlier than" formats (which tend to be more restrictive).

- The desired time of collection. This restraint lets the collection system know that the value or quality of the collected intelligence is at least partially dependent upon the time in which it is collected. Formats in common use tend to specify a point in time, identify a time window during which collection should be accomplished, or require that collection be accomplished continuously for some length of time (in this situation the collection function becomes more of a surveillance function).

These technical restraints, similar to the quality subrequirements, must be expressed with respect to the specific collection subsystems and eventually their collection platforms. There exist other technical restraints associated with any given collection subrequirement. These will not be specifically addressed in this thesis but are considered in all algorithm development.

A single collection subrequirement if portrayed graphically (and decomposed to the collection subsystem level) would contain information describing where it originated (some sort of tag associating it with a user or set of users), the quality or nature of the subrequirement, the collection subsystem it is associated with, and all appropriate technical restraints. The structure of a subrequirement might look like that shown at Figure 4.4. As previously mentioned, the decomposition of collection requirements is traditionally accomplished by the collection subsystem relying heavily upon expert judgement and prior practices/standard procedures. Therefore the subrequirement structure depicted above should be viewed at this point in the thesis as a tool to enhance understanding of a collection subrequirement.

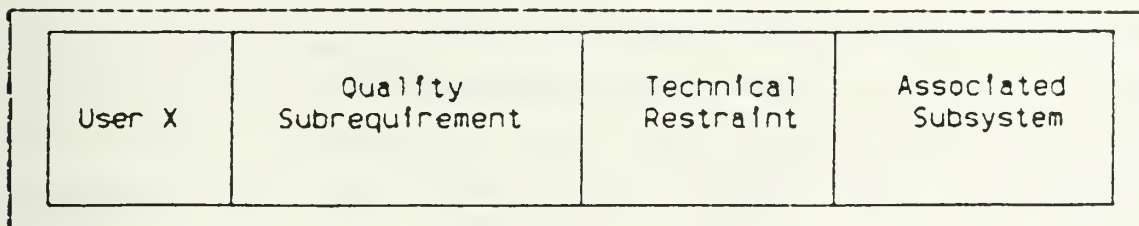


Figure 4.4 Subrequirement Structure.

If one were to group all of a single collection requirement's subrequirements into one construct it might appear as that shown in Figure 4.5. The collection system, in this case, consists of three collection subsystems - 1, 2, 3. The collection requirement originated from unit number 2 and was decomposed by the collection subsystems into three subrequirements.

Unit	Subreq	Tech Restraint	Subsystem
1st Bde	Subreq 1	Best Possible	SIGINT
1st Bde	Subreq 2	NLT 1000 Hrs	Surveillance
1st Bde	Subreq 3	0800 to 1000	HUMINT
1st Bde	Subreq 4	Best Possible	Photo/IR

Figure 4.5 Collection Requirement Vector.

It could be demonstrated, using an example of collection platform requirement decomposition, how this process can

continue to the highest levels of resolution. However, this study is focused on the relationship between the collection system and subsystem and will not, therefore, develop the decomposition methodology any further than that already presented.

D. THE INTELLIGENCE COLLECTION MANAGEMENT PROBLEM

The collection management problem is a resource allocation problem. Scarce collection resources must be allocated toward the satisfaction of collection requirements. This thesis suggests that the traditional approach to that problem (as depicted at Figure 4.3 and discussed in previous chapters) can be improved greatly with some minor modifications to the functional structure of the current system and the use of a mathematical optimization scheme. The structural modification (and resulting efficiencies) is straightforward and will be addressed in the following paragraph. The optimization scheme is more complicated and will be developed in Chapter Four.

The primary functional change suggested by the previous discussion is that of allocating collection resources to satisfy collection requirements (and perhaps subrequirements) from the collection system rather than the collection subsystem level. In order to perform this allocation function collection systems must possess the capability of matching subrequirements to collection subsystems (hence a requirement decomposition capability). We will assume for the remainder of this study that such a capability can be transferred from the subsystem to system level with little difficulty.

Certain efficiencies and advantages result from this consolidation function. With this new structure requirements need not be addressed by all collection subsystems.

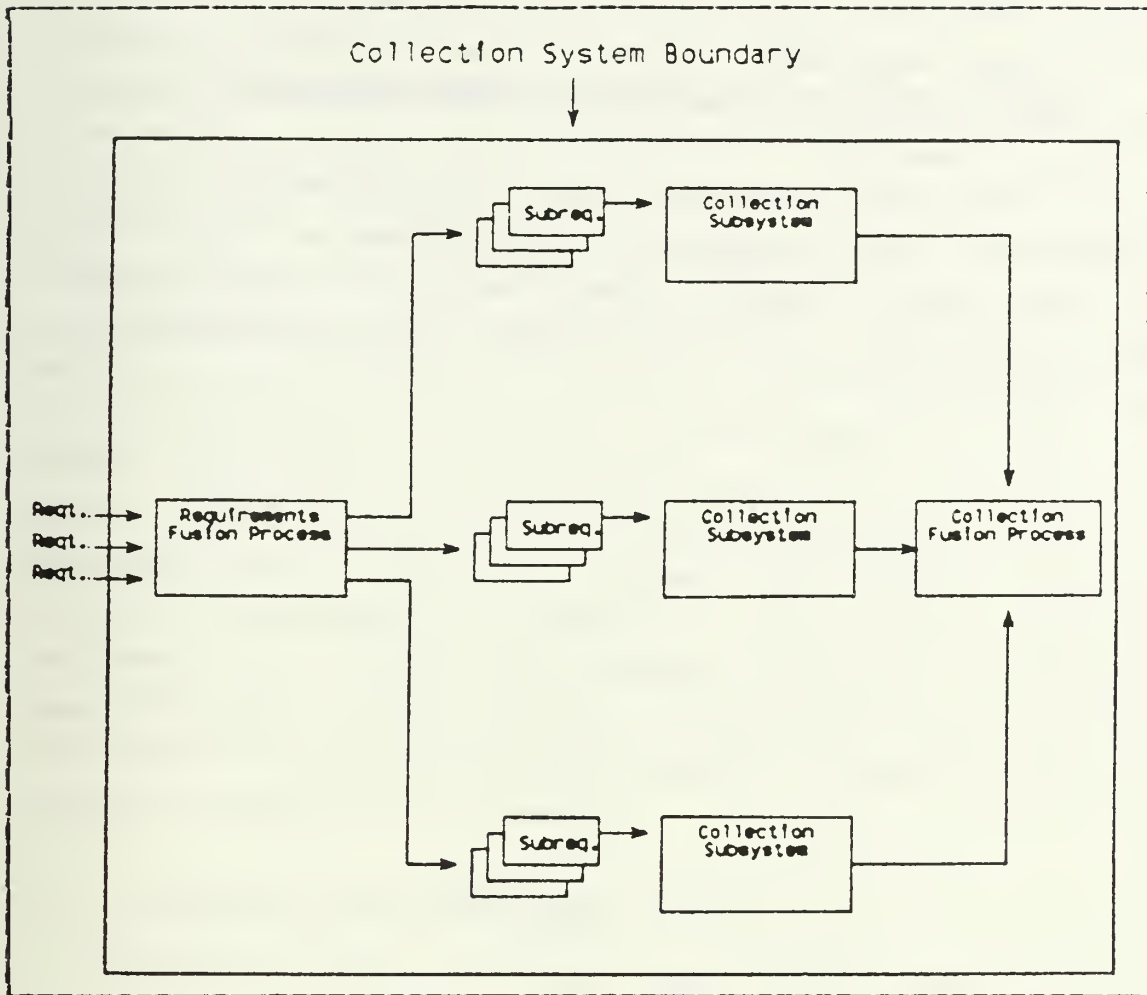


Figure 4.6 Restructured Collection System.

Only those requirements (or subrequirements) best suited for satisfaction by a subsystem would be forwarded to that subsystem for collection action. Unwanted duplication of effort could be more easily limited with this structure. A more balanced use of all collection subsystems could be controlled from the collection system level. These efficiencies are important but of a fairly administrative nature.

The real advantage of this structure is that it allows for the application of optimization methods to the

collection resource allocation problem. At this point in the collection management process we are now aware of the demands (in the form of requirements) placed upon the system and of our resource constraints (available collection assets). With some added input from the collection subsystems concerning their operational capabilities we will be in a position to apply powerful optimization procedures to the allocation problem. These procedures will be addressed in Chapter Five.

V. THE INTELLIGENCE COLLECTION MANAGEMENT MODEL

This thesis suggests than an examination and analysis of intelligence collection requirements prior to the actual allocation of collection platform resources will lead to a more intelligent and efficient use of such resources. This portion of the study will develop a mathematical optimization model which is useful in the performance of such analysis. Initially, a simplified version of the collection system will be considered in the development of this model. Modifications to the basic model will address important intelligence collection concerns. The subject this model addresses is that of scarce resource allocation. Specifically, in what manner should available collection resources be allocated to best satisfy a given set of intelligence collection requirements.

A. THE BASIC COLLECTION SYSTEM MODEL

The basic collection system model is described below:

$$\begin{aligned} \text{MAXIMIZE:} \quad & \sum_{i=1}^n v_i E_i \\ \text{SUBJECT TO:} \quad & \sum_{i=1}^n a_{ij} d_{ij} \leq b_j \quad \forall j \quad (\text{eqn 5.1}) \\ & E_i = f(d_{ij}) \\ & d_{ij} = 0 \text{ or } 1 \end{aligned}$$

$i = 1, \dots, n$ (i is the index for collection requirements. There are a total of n collection requirements considered in the requirement set of the basic model)

$j = 1, \dots, m$ (j is the index for collection subsystems. There are a total of m collection subsystems considered in the basic model)

d_{ij} = The decision to allocate collection resource j to collection requirement i ($0 = \text{no}$, $1 = \text{yes}$).

a_{ij} = The amount of collection resource j allocated toward the satisfaction of collection requirement i if $d_{ij} = 1$ (units are subsystem collection hours - hrs).

b_j = Total amount of subsystem j collection resources available for use in satisfying the set of collection requirements n .

v_i = Relative importance associated with requirement i (priority). Requirement priority will not be considered in the basic model and therefore $v_i = 1$ in the basic model. Requirement priority will be addressed in Section B.2 of this Chapter where values of v_i will be allowed to vary.

E_i = Expected fraction of requirement i satisfied by those collection subsystems ($j = 1, \dots, m$) tasked to satisfy that requirement.

Certain assumptions associated with this model should be addressed. The simplified collection system which will be the basis for model development has as one of its characteristics a fixed number, m , of collection subsystems. Let s_j be defined in the following manner:

s_j = collection subsystem j (for $j = 1, \dots, m$).

Therefore j is the index for collection subsystems. The impact of the fixed collection subsystem assumption is that the quantity of collection subsystems available for operational employment by the decision maker does not change during the course of the collection resource allocation decision process. This collection system will also only consider a fixed quantity, n , of collection requirements. Let r be defined in the following manner:

r_i = The i th collection requirement (for $i=1, \dots, n$).

Thus, i is the index for collection requirements. In other words, the number of collection requirements under consideration does not change during the course of the resource allocation process. An additional assumption closely related to the fixed number of requirements assumption concerns the timing of the collection decision. For the basic model it is assumed that all of the collection requirements under consideration (r_1, r_2, \dots, r_n) will have collection resources allocated for their satisfaction at the same time. Furthermore, the results (collected data) from all collection subsystems (s_1, s_2, \dots, s_m) will reach the appropriate user within the bounds of the required time restraints. In other words, the lead and lag time considerations addressed in previous chapters are not considered in the basic model.

1. Decision Variables

The decision variable used in the basic model is binary:

$$d_{ij} = \begin{cases} 0 & \text{if subsystem } j \text{ does not allocate collection resources to satisfy requirement } i. \\ 1 & \text{if subsystem } j \text{ does allocate collection resources to satisfy requirement } i. \end{cases}$$

This implies that the basic model will only determine whether or not it should allocate a predetermined and fixed amount of collection resource from subsystem j toward the satisfaction of requirement i . The importance of this assumption and decision rule are great. It does not allow the model to vary the amount of collection resource it allocates toward the satisfaction of a requirement. It either allocates a fixed and predetermined amount of resource (a_{ij}) or none at all. Collection subsystems, in other words, can only attempt to satisfy a collection requirement by allocating resources in one specific manner. At first glance, the use of this type of decision variable seems to be a harsh and unrealistic constraint on the model. Such a perception is inaccurate.

The great majority of tactical intelligence requirements fall into one of several classes of requirements. Targeting requirements form such a class. In order to satisfy a targeting requirement the collection system must basically provide the user (requestor) with information concerning the location, dispersion, nature (its type of activity), and level of protection (armored or not) of a potential target. Collection subsystems which possess the capability of at least partially satisfying targeting requirements have developed SOPs (standard operating

procedures) for attempting such satisfaction. For the majority of such targeting requirements these SOPs are closely adhered to by the subsystems. In special targeting situations (as in nuclear packages), of course, special subsystem allocations can be planned and employed. This, however, is the exception rather than the rule. Similar procedures are followed for other classes of collection requirements.

The model assumption that subsystems can only satisfy a requirement in one particular manner is, in fact, more closely related to the realistic setting than previously expected. It applies to the majority of typical collection requirements. Thus, the basic model developed in this study should be considered applicable to such classes of requirements.

There exist collection requirements to which the decision variable d_{ij} is not well suited. Certain requirements, for instance, can be satisfied by collection subsystems at varying levels of satisfaction rather than at a single discrete level of satisfaction as suggested in the basic model. An example of such a subsystem might be that of the signal intelligence collection subsystem. Clearly, the level of satisfaction of certain requirements would increase (to a point of diminishing marginal returns) as more hours of signal intercept time are applied to the satisfaction of the requirement. We would also suspect that this level of effectiveness function might be continuous and monotone increasing (i.e. 1.5 hours of intercept time cannot be less effective than 1.0 hours of intercept time). In such situations a more suitable decision variable x_{ij} should be used.

x_{ij} = The amount of collection resource from subsystem j allocated toward the satisfaction of requirement i .

The application of this type of decision variable to the basic model will be addressed in Section B.4 of this chapter.

2. Resource Constraints

In the basic model it will be assumed that each collection subsystem j has at its disposal a fixed amount of collection resources. Let b_j be defined in the following manner:

b_j = The total amount of subsystem j collection resources available for allocation toward the satisfaction of collection requirements.

Thus, b_j is a constant in the basic model. The units of b_j are subsystem collection hours. Thus, the overall resource constraints of this model can be represented in the following manner:

$$\sum_{i=1}^n d_{ij} a_{ij} \leq b_j \quad \forall j \quad (j = 1, \dots, m) \quad (\text{eqn 5.2})$$

Let a_{ij} be defined in the following manner:

a_{ij} = The amount of collection resource j allocated toward the satisfaction of collection requirement i if $d_{ij} = 1$ (in subsystem collection hours).

The relationship between collection subsystems and collection requirements is critical to this model. Specifically, collection subsystems, in the allocation of their specific collection resources, contribute to the satisfaction of intelligence collection requirements. There

are several ways in which intelligence collection resources can be allocated. For example, aerial reconnaissance subsystem resources are normally allocated in terms of the number of sorties per requirement. Signal intelligence subsystem resources, on the other hand, are often allocated in terms of the number of positions (where the term position refers to operator position) and the quantity of monitoring time per requirement. These examples indicate that collection resource units can be very diverse. In order to consider the multiple collection subsystem resources in the basic model it must be shown that diverse collection resource units can be transformed (in a somewhat reasonable manner) into subsystem hours. The two examples cited in this paragraph can easily be transformed into similar units (i.e. subsystem collection hours).

A typical aerial reconnaissance sortie may last three hours. Of that three hour time period perhaps only one hour can be used for actual reconnaissance time (this reconnaissance time is normally referred to as time on target or TOT). If, during this one hour TOT, the platform performed its aerial reconnaissance mission against two collection requirements, then that subsystem could be said to have allocated .5 subsystem collection hours to each of the two collection requirements. Note that the calculated number of subsystem collection hours was independent of whether or not the aerial reconnaissance subsystem achieved success in its mission effort. Therefore, for this specific subsystem the following relationship holds:

$$a_{ij} = \frac{\text{amount of TOT (hours)}}{\text{\# of intelligence requirements collected against while on target}} \quad (\text{eqn 5.3})$$

In this sense a_{ij} can be interpreted as equaling the number of aerial reconnaissance subsystem collection hours consumed in attempting to contribute to the satisfaction of collection requirement i .

Tactical signal intelligence subsystems typically have at their disposal many operators (analysts) who extrapolate from intercepts and other signal data information relevant to the satisfaction of collection requirements. Each operator is able to work a fixed amount of hours performing his function. If two subsystem operators each must spend four hours performing their function in attempting to contribute to the satisfaction of a given collection requirement then eight subsystem collection hours have been allocated to that requirement. The following relationship holds with respect to this collection subsystem:

$$a_{ij} = \frac{\text{(amount of subsystem hours per position)} \times \text{(number of positions)}}{\text{(number of intelligence requirements collected against)}} \quad (\text{eqn 5.4})$$

The interpretation of a_{ij} is similar to that of the preceeding example - the number of signal intelligence subsystem collection hours consumed in attempting to contribute to the satisfaction of collection requirement i .

It is a simple matter to make allocation calculations once collection has already occurred. If the collection model is to be useful, however, it must be able to aid the decision maker prior to the actual allocation of collection resources. To do so this model therefore requires that a_{ij} values be known or estimated prior to the resource allocation decision. How can this a priori estimation of a_{ij} be accomplished?

The first and perhaps most simple approach to this problem is to have the subsystem j operators subjectively estimate a_{ij} given requirement i . The advantage to this technique is that the expertise of the subsystem operators is applied to the a_{ij} estimate. There are, however, many disadvantages. Included among them are inconsistencies and inaccuracies associated with subjective estimates (even when competent personnel are providing the estimates) and variations in levels of expertise found among the operators of a given subsystem. Thus, the primary disadvantage to the subjective estimation of a_{ij} is that the quality of the estimate is far too dependent upon the quality of the operator providing that estimate.

A second method of handling this estimation problem is through the establishment and use of norms and standard operating procedures (SOPs) which are known to be accurate or at least reasonable. For instance, a SOP may, based upon previous experimental data and experience, specify that only a predetermined amount (with no variation) of subsystem collection hours associated with collection subsystem j will be allocated toward the satisfaction of any given collection requirement i . For example, such an SOP might allow for the allocation of only one aerial reconnaissance sortie (one subsystem collection hour) for any single collection requirement. In this sort of a system the estimation of a_{ij} is really no estimation at all but rather a decision rule used by the collection system decision maker. The value of such a system depends upon its ability to accurately match all requirements with appropriate SOPs. The potential weakness of such a system depends on its ability to handle diverse types and classes of collection requirements.

A third method involves the use of both techniques addressed above. This technique allows for the subjective estimation of a_{ij} (by expert subsystem operators) which are

at the same time bounded by norms and SOPs. For example, an aerial reconnaissance subsystem operator may be authorized to make a_{ij} estimates of integer subsystem collection hours less than three. In other words, he is not authorized to provide non-integer estimates or estimates of allocations of three hours or more. This technique is often used in practice where collection subsystem characteristics often dictate a finite set of possible collection allocations (and would therefore dictate estimates of a_{ij} in the basic model). This system appears to provide a reasonable approach to the problem of a priori estimation of a_{ij} . The wide range of possible collection resource allocation estimates is narrowed by subsystem operating procedures, norms, and standards. Individuals are then in a better position to provide more accurate estimates of a_{ij} .

From this discussion we conclude that the estimate of the amount of subsystem collection hours associated with collection subsystem j in contributing to the satisfaction of collection requirement i (a_{ij}) can be provided by the specific subsystem operators. Furthermore, such an estimate is highly dependent upon the manner in which a specific collection subsystem can allocate collection resources.

3. Objective Function

There are two major components of the objective function in the basic collection model. The first, v_i is defined as follows:

v_i = The relative importance associated with a given collection requirement i (priority).

In the basic model the value for all v_i will be equal to one. Thus, an assumption inherent in the basic model is that all requirements to be satisfied are of equal relative importance (equal priority).

The second major component of the objective function is E_i .

E_i = The aggregated effectiveness of requirement i with respect to all collection subsystems.

This component, in turn, is dependent upon several other factors which will be developed in the following paragraphs. The first factor in the determination of aggregated effectiveness pertains to the effectiveness of a collection subsystem j . In attempting to satisfy a given collection requirement i , collection subsystem j interacts with some measurable form of enemy activity. For instance, a photo reconnaissance platform takes a picture of a location on the battlefield (presumed to be located in enemy territory). A communications intercept platform monitors certain frequencies on the electromagnetic spectrum (hopefully the enemy is transmitting information of value which friendly forces can detect on such frequencies). Many things can happen which can prohibit these interactions from occurring. In the photo reconnaissance situation, for example, the platform may breakdown prior to its TOT or worse yet may be shot down by the enemy. In the communications intercept case the enemy may decide to operate on radio silence (i.e. not use those monitored frequencies at all). In both situations, the collection effort would be unsuccessful. As a matter of fact, the intended interaction with enemy activity did not occur at all (or we cannot detect whether it occurred). When this happens we say that the collection mission has failed. There exist measures or estimates of these sorts of failures with respect to different types of collection platforms and subsystems under a variety of threat and operational conditions. These measures are often represented as a probability. In our situation we are specifically interested in the probability of mission failure (where mission

is defined as collecting the information/data, etc. that the platform or subsystem intended to collect). In this basic model we are concerned with the probability of success rather than failure and define the term p_{ij} in the following manner:

p_{ij} = The probability that collection subsystem j will collect the data it intends to collect in attempting to satisfy a requirement i .

Notice that this definition does not imply that the collection subsystem actually was able to satisfy the collection requirement.

The second factor which is important in determining the effectiveness of a collection subsystem pertains to actual satisfaction of the collection requirement. Recall that a collection subsystem may be capable of satisfying all, none, or a portion of any given collection requirement. The term f_{ij} is defined as:

f_{ij} = That fraction of requirement i which can be satisfied if collection subsystem j collects the data it intends to collect in attempting to satisfy requirement i .

Note that the term f_{ij} is of the form of a conditional expected fraction. Consider the example in which a collection requirement consists of four primary parts (these were referred to as quality subrequirements in previous chapters). The aerial reconnaissance system, in this example, could satisfy two of those four subrequirements if it successfully performed its collection mission (collected the data it intended to collect). Thus, in this example, the calculated value for f_{ij} would be 0.5.

For simple classes of requirements the determination of the value of f_{ij} is a fairly simple matter (as

demonstrated in the example in the preceeding paragraph). For such simple classes of requirements and various types of collection subsystems it would be theoretically possible to develop norms and standards useful in determining such values. For example, in the class of simple targeting requirements cited in an earlier paragraph, only three items of information were required for satisfaction - target description, nature, and level of protection. For this simple class of requirements the aerial reconnaissance subsystem is capable of satisfying all of the subrequirements given that the intended collection occurs. Therefore its f_{ij} value with respect to simple targeting requirements is one. For more complicated classes of collection requirements we would expect that the determination of f_{ij} will be more difficult. In the basic model under consideration it will be assumed that it is possible to determine the values of all f_{ij} for the requirements under consideration.

The term which represents the relationship between satisfaction of a given collection requirement i by collection subsystem j can now be identified and examined. The term e_{ij} is defined as expected level of requirement satisfaction as given by:

$$e_{ij} = p_{ij} \cdot f_{ij} \quad (\text{eqn 5.5})$$

This term can be interpreted in the following manner: If collection system j is allowed to allocate resources toward the satisfaction of requirement i , then e_{ij} represents the level of collection requirement satisfaction we might expect to receive in return. The calculation of e_{ij} is of the form

of a probability multiplied by a conditional expected fraction (both values are bounded by zero and one) yielding an expected value. Thus e_{ij} is also bounded by zero and 1.

The value e_{ij} represents the level of requirement satisfaction we would expect to receive by allocating resources from a single collection subsystem j against a single collection requirement i . Our problem, however, involves multiple collection requirements and subsystems. In order to solve this problem we must be able to aggregate over both requirements and subsystems. We will first attempt to deal with the total effectiveness of a given collection requirement.

a. Aggregation Over Collection Subsystems

Let E_i be defined in the following manner:

E_i = The expected fraction of requirement i satisfied by all collection subsystems ($j = 1, \dots, m$).

This study will address two possible methods of obtaining the total aggregated effectiveness - denoted E_i .

The first approach to the calculation of E_i is through the simple summation of e_{ij} values and will be denoted E_i^1 . Specifically:

$$E_i^1 = \sum_{j=1}^m e_{ij} d_{ij} \quad (\text{eqn 5.6})$$

Under most envisioned circumstances one would not expect to ever be able to satisfy a requirement by any factor greater

than 100%. Unfortunately, this specific method of aggregation allows for that to occur. Consider the simple example in which a given collection requirement can be satisfied by two collection subsystems. In this example the value of e_{i1} is .75 and e_{i2} is .50. If the decision is made that both subsystems will allocate their resources toward the satisfaction of that i th requirement, then according to the summation procedure the total expected level of satisfaction for that i th requirement would be:

$$\begin{aligned}
 E_i^1 &= \sum_{j=1}^2 e_{ij} d_{ij} \\
 &= (e_{i1} \cdot d_{i1}) + (e_{i2} \cdot d_{i2}) \\
 &= (.75 \cdot 1) + (.50 \cdot 1) \\
 &= \underline{\underline{1.25}}
 \end{aligned}
 \tag{eqn 5.7}$$

This value seems difficult to interpret given the preceeding development. An obvious explanation for the E_i^1 value greater than one is that there must exist some amount of collection subsystem overlap. This overlap is referred to a redundant coverage. The summation technique would provide more reasonable results if only one collection subsystem were allowed to allocate resources toward the satisfaction of a collection requirement. If this condition were to be applied to the example above then the collection requirement in question would have a total expected level of

satisfaction equal to either E_i^1 (.75) or E_i^1 (.50). Of course, this is not an aggregation scheme at all. Another situation in which the summation technique may be a reasonable method of aggregation is when we are certain that there is no possible way in which the same portion of a collection requirement can be satisfied by more than one collection subsystem. In other words, for a given requirement i , the f_{ij} value associated with one collection subsystem j must not intersect with the f_{ij} value associated with any other collection subsystem j . The two values, in a probabilistic sense, must be mutually exclusive. An example of such a situation might involve a collection requirement such as:

- What types of communications systems is the unit located at ABxxxxxx using?

It is likely that this requirement might be satisfied by tasking sensors which could detect and locate communications emitters on separate and non-overlapping portions of the electromagnetic spectrum. Thus, no more than one sensor or subsystem could satisfy the same portion of the collection requirement. The f_{ij} values associated with this requirement and their respective subsystems would be mutually exclusive and the summation methodology would be a reasonable method of aggregation.

A second drawback to the summation method of aggregation is that there exists, using this technique, no way to represent, in a continuous sense, decreasing marginal returns. Specifically, the summation function tells us that more resource allocation to requirements with high values of E_i^1 is always a good thing to do. In fact, we can see that there are many circumstances where this action is not a good thing to do. Clearly, there exists some point in time in which additional resource allocation to satisfy a requirement which may already be totally satisfied is not productive and in fact is wasteful.

Thus, for reasons of interpretability and because the summation function lacks a way of representing decreasing marginal returns we reject it as a method of aggregating values of e_{ij} over collection subsystems. The next method of aggregation provides a solution to these two difficulties.

The primary drawback to the previous aggregation scheme is that under certain conditions it would produce aggregated effectiveness values which were difficult to interpret and could not adequately represent decreasing marginal returns associated with the allocation of collection resources. A more meaningful scheme would be one in which the total expected level of satisfaction for a given requirement (when collected against by multiple subsystems) would be bounded by one and could thus be more easily compared with percent levels of requirement satisfaction (i.e. 100% satisfaction would be the maximum attainable value for E). Furthermore, we would like to see the total expected level of requirement satisfaction increase as more collection subsystems are tasked toward the satisfaction of a given collection requirement but not necessarily in a totally linear fashion. In other words, two collection subsystems ought to provide more satisfaction than one but they could never provide more than 100% requirement satisfaction. Intuitively we would expect that the lower bound on the expected level of requirement satisfaction (in the case where two subsystems were tasked to satisfy a given collection requirement) would be the maximum of (e_{i1}, e_{i2}) .

If we interpret the value of $(d_{ij} \times e_{ij})$ as the probability of achieving satisfaction of requirement i by allocating collection resources from subsystem j then the term:

$(1 - d_{ij} e_{ij})$ = The probability of not achieving satisfaction of requirement i by allocating collection resources from subsystem j (given that we decide to allocate resource from j).

If we also consider that the operation of one collection subsystem is independent of the operation of another then the probability of not achieving satisfaction of requirement i by allocating collection resources from m collection subsystems can be represented in the following expression:

$$\prod_{j=1}^m (1 - d_{ij} e_{ij}) \quad (\text{eqn 5.8})$$

Of course, the probability of achieving satisfaction of requirement i by allocating collection resources from m collection subsystems is actually E_i which, in turn, is given by:

$$E_i = \left(1 - \prod_{j=1}^m (1 - d_{ij} e_{ij}) \right) \quad \forall i \quad (\text{eqn 5.9})$$

This second technique of aggregating e_{ij} values does indeed deal with the shortcoming of the summation methodology. Specifically, E_i values are bounded between zero and one and the effects of diminishing marginal returns are inherent in the nonlinear nature of the product function.

The primary cause for concern with respect to this aggregation technique is the assumption of independence of collection subsystems. We are concerned that two or more subsystems, in collecting information pertaining to the same requirement, might be dependent upon one another. This possibility does exist. Say, for instance, an aerial reconnaissance platform overflies an enemy position on a collection mission. The enemy, in response to that overflight, ceases all electronic emission activity (fearing the platform was capable of detecting such activity). An electronic intercept platform collecting that enemy unit's emissions would be negatively affected by the aerial reconnaissance platform's overflight.

Examples such as these are hard to envision but in fact much of the intelligence operation planning process is devoted to insuring that two or more collection operations do not conflict or interrupt one another. The point to be made is that this method of aggregation seems to be a reasonable approach as long as the collection subsystems involved are independent of one another.

b. Aggregation Over Collection Requirements

We must now concern ourselves with the second aggregation problem. How do we combine E_i^2 for all collection requirements under consideration? Let E be defined in the following manner:

E = Total level of requirement set (n requirements) satisfaction given collection allocation from m subsystems.

$$E = \sum_{i=1}^n v_i \left(1 - \prod_{j=1}^m (1 - d_{ij} e_{ij}) \right) \quad (\text{eqn 5.10})$$

In this model we are summing (over all requirements) the expected level of satisfaction for requirement i values (Equation 5.9) developed in a previous discussion. The range of this new value would fall between zero and n (the total number of requirements equals n). One weakness of this representation as a measure of total requirement set satisfaction lies in the fact that the summed values are somewhat difficult to interpret. For instance, one has no way of determining (from this value alone) which requirements in a given set might be highly satisfied and which requirements in the same set might not be highly satisfied. In other words one should examine the variance of the values of E_i^2 . In the simple model we are primarily concerned with the aggregate level of requirement satisfaction and will not concern ourselves with levels of satisfaction of individual requirements. In Section B.2 of this chapter we consider the case in which collection requirements are not assumed to be of equal importance and hence are concerned with varying levels of requirement satisfaction. An additional shortcoming is that the formulation assumes that there is no overlapping of collection requirements. Most collection systems indirectly guard against this sort of overlap by grouping together (piggy-backing) similar requirements into a common single requirement. Thus, we do not consider such overlap to cause major difficulties with respect to the model. Therefore, despite interpretability and overlaps shortcomings, summation does appear to be a reasonable method of aggregating the levels of effectiveness of n collection requirements.

4. Comments on the Basic Model

The basic model as formulated will attempt to allocate collection subsystem resources to requirements in a manner which provides the biggest return in overall E (total

aggregated level of requirement satisfaction) for a given allocation (assuming a feasible solution can be found for the program). Thus, resource allocations will be made to those requirements whose E_i^2 contribute the most to the objective function. The amount of E_i^2 which any single requirement can contribute to overall satisfaction (E) increases as more resources are allocated toward the satisfaction of the requirement but reaches a limit of one. This characteristic results from the manner in which E_i^2 is calculated. Recall Equation 5.9. As more collection resources are allocated to the satisfaction of requirement i the product term in Equation 5.9 becomes small. The term E_i^2 , therefore, approaches one as a limit in such circumstances. Thus, as more resources are allocated the marginal return of such allocation decreases until such time as allocation to a different requirement becomes more attractive.

One disturbing aspect of this basic model is that we have no guarantee that all requirements in the given set will be satisfied by the optimum resource allocation scheme calculated by the program. For instance, allocation of collection resources to a given requirement may never be more attractive (contribute more to the maximization of the objective function) than allocations to other collection resources. In such a situation this program would ignore requirement i in favor of allocations of resources to other requirements. An additional limitation (somewhat related to the first) is that we have no control over the level of satisfaction of any given or set of collection requirements. In other words this program cannot deal with requirement priorities.

E. VARIATIONS OF THE BASIC MODEL

Recall the basic model developed in the first section of this chapter:

$$\begin{aligned} \text{MAXIMIZE:} \quad & \sum_{i=1}^n v_i E_i \\ \text{SUBJECT TO:} \quad & \sum_{i=1}^n a_{ij} d_{ij} \leq b_j \quad \forall j \quad (\text{eqn 5.11}) \end{aligned}$$

$$d_{ij} = 0 \text{ or } 1$$

$i = 1, \dots, n$ (i is the index for collection requirements. There are a total of n collection requirements considered in the requirement set of the basic model)

$j = 1, \dots, m$ (j is the index for collection subsystems. There are a total of m collection subsystems considered in the basic model)

d_{ij} = The decision to allocate collection resource j to collection requirement i ($0 = \text{no}$, $1 = \text{yes}$).

a_{ij} = The amount of collection resource j allocated toward the satisfaction of collection requirement

i if $d_{ij} = 1$ (units are subsystem collection hours - hrs).

b_j = Total amount of subsystem j collection resources available for use in satisfying the set of collection requirements n .

v_i = Relative importance associated with requirement i (priority). Requirement priority will not be considered in the basic model and therefore $v_i = 1$ in the basic model. Requirement priority will be addressed in Section B.2 of this Chapter where values of v_i will be allowed to vary.

E_i = Expected fraction of requirement i satisfied by those collection subsystems ($j = 1, \dots, m$) tasked to satisfy that requirement.

1. Insuring Levels of Requirement Satisfaction

A primary drawback to the basic model can be handled using a similar problem formulation. If possible we would like to be able to satisfy all collection requirements in the total set. In order to insure this we could add to the above formulation additional non-negativity constraints. A modified formulation containing such restraints is described below:

$$\text{MAXIMIZE:} \quad E = \sum_{i=1}^n v_i E_i^2$$

$$\text{WHERE:} \quad E_i^2 = 1 - \prod_{j=1}^m (1 - d_{ij} e_{ij})$$

SUBJECT TO:

$$E_i^2 \geq k_i$$

(eqn 5.12)

$$\sum_{i=1}^n d_{ij} a_{ij} \leq b_j \quad \forall j$$

$$d_{ij} = 0 \text{ or } 1$$

k_i = An aspiration level of individual requirement satisfaction.

This formulation will insure levels of E_i^2 greater than k_i for all collection requirements i (at least some minimum level of requirement satisfaction). We remain uncertain, however, of the ultimate level of requirement satisfaction. One can easily imagine an iterative type process which would increment the value of k_i between successive runs of the program until a feasible solution can no longer be obtained. The goal of this iterative process would be to determine the highest levels of satisfaction at which all requirements could be feasibly satisfied. One must realize that the final levels will be dependent upon the scaling factors (k_1, k_2, \dots, k_n) imposed by the program.

There is a fundamental difference between this model and the basic model outlined in Section A of this Chapter. The basic model is guaranteed to have a feasible solution. All requirements in the set may not be satisfied to a minimally desirable level but the model will find a solution. The constraints placed upon the basic model (as outlined in this section) may eliminate the possibility of finding a feasible resource allocation scheme.

Given this fact it may be reasonable to approach the solution of this problem in an iterative manner.

Specifically, use the solution to the basic model as a starting point upon which small iterative improvements (through the increase in k_i values) are made. This approach in itself does not guarantee a feasible solution. It does, however, allow for the initial introduction of k_i constraints into the problem at low levels which will hopefully lead to feasible allocation solutions. A primary drawback to this approach is that it requires some level of human interaction which, of course, slows down the process of solving the problem.

A different approach to this same problem is to formulate the model in the following manner:

MAXIMIZE: Z

SUBJECT TO: $(1 - \prod_{j=1}^m (1 - d_{ij}e_{ij})) > Zk_i$

$$\sum_{i=1}^n d_{ij}a_{ij} \leq b_j \quad \forall j \quad (\text{eqn 5.13})$$

$$d_{ij} = 0 \text{ or } 1$$

Zk_i = The highest attainable level of individual requirement satisfaction.

The value Z in this formulation serves as a scalar multiple of the individual requirement aspiration levels (k_i). Thus, this formulation maximizes the value of Z and in doing so maximizes the the level of individual requirement

satisfaction subject to the aspiration levels (k_1, k_2, \dots, k_n) imposed on the program.

2. Requirement Priorities

The prioritization of collection requirements serves as an important management function and, as Appendix A suggests, as a possible means of providing intelligent control of the collection process. We know that it is possible to prioritize a given set of collection requirements (see Appendix A). We must be able to incorporate some such ranking scheme into the optimization process.

There are two approaches toward modifying the basic model once we have decided that one requirement may be more important than another. The first approach is to insure that the more important requirement is allocated collection resources in such a manner that its level of satisfaction (E_i^2) is greater than that of the less important requirement. The second approach is to insure that the objective function of the model takes into account the fact that one requirement is more important than the other when it maximizes the overall level of requirement set satisfaction (E). Each of these two approaches are addressed in the following sections.

a. Prioritizing Using Levels of Requirement Satisfaction

There are several approaches to insuring more important requirements achieve higher levels of requirement satisfaction than less important requirements. Taking the formulation developed in Equation 5.12:

$$\text{MAXIMIZE: } E = \sum_{i=1}^n v_i \left(1 - \prod_{j=1}^m (1 - d_{ij} e_{ij}) \right)$$

$$\text{SUBJECT TO: } E_{i(h)}^2 \geq .9$$

$$E_{i(m)}^2 \geq .7$$

$$E_{i(l)}^2 \geq .5$$

$$\sum_{i=1}^n d_{ij} a_{ij} \leq b_j \quad \forall j$$

$$d_{ij} = 0 \text{ or } 1$$

We have modified the program at Equation 5.12 by creating constraints which correspond to the levels of priority in our priority system (in this case there are three priorities - high(h), medium(m), and low(l)). Specifically, we have determined that we desire that the high priority requirements in the total set be satisfied at the .9 level, medium priority requirements at the .7 level, and low priority requirements at the .5 level. Certain aspects of this formulation cause concern. That concern revolves around the relationship between low, medium, and high priority requirements. For example, in the above formulation we require $E_{i(l)}^2$ for all low priority requirements must be greater than or equal to .5 and those for medium priority requirements be satisfied at a level greater than or equal to .7. As a result of these constraints we should expect to see that high priority requirements are satisfied at values greater than or equal to the value .9. What we do not know is what will happen to our overall E (and satisfaction

levels for high and medium priority requirements) in the event we lower the constraints for low priority requirements from .5 to value .2. Similarly we don't know what will happen if we merely drop one low priority requirement from the total set of requirements.

This observation suggests that we examine the sensitivity of the manner in which we allocate resources to collection requirements. One way to accomplish this sort of examination is to approach the prioritization of the collection requirement set in a somewhat different manner. Suppose we partition the rank ordered requirement vector (R) returned by the process outlined in Appendix A into three sections - R_l , R_m , R_h . High priority requirements are elements of R_h , medium priority requirements are elements of R_m , and low priority requirements are elements of R_l . It is certainly desirable that high priority requirements (R_h) be allocated resources in such a manner that their respective levels of satisfaction are high. To insure that this can be accomplished, irrespective of all R_m and R_l requirements, we formulate the following:

$$\text{MAXIMIZE:} \quad E = \sum_{i=1}^n v_i \left(1 - \prod_{j=1}^m (1 - d_{ij} e_{ij}) \right)$$

$$\text{SUBJECT TO:} \quad E_i^2 \geq .9 \quad \forall_i \in R_h \quad (\text{eqn 5.15})$$

$$E_i^2 \geq 0.0 \quad \forall_i \in (R_m, R_l)$$

$$\text{WHERE:} \quad E_i^2 = \left(1 - \prod_{j=1}^m (1 - d_{ij} e_{ij}) \right)$$

$$\sum_{i=1}^n d_{ij} a_{ij} \leq b_j \quad \forall j$$

$$d_{ij} = 0 \text{ or } 1$$

If such a program proves to provide a feasible solution then we will know exactly what levels of satisfaction (E_i^2) for all requirements and that those requirements we identified as having a high priority will have E_i^2 values of at least .9. The next step in the iterative process is to add levels of satisfaction constraints to the program for those requirements we have identified as having a medium priority. This formulation would appear as follows:

$$\text{MAXIMIZE:} \quad E = \sum_{i=1}^n v_i \left(1 - \prod_{j=1}^m (1 - d_{ij} e_{ij}) \right)$$

$$E_i^2 \geq .9 \quad \forall i \in R_h$$

$$E_i^2 \geq .7 \quad \forall i \in R_m$$

$$E_i^2 \geq 0.0 \quad \forall i \in R_l \quad (\text{eqn 5.16})$$

$$\text{WHERE:} \quad E_i^2 = \left(1 - \prod_{j=1}^m (1 - d_{ij} e_{ij}) \right)$$

$$\sum_{i=1}^n d_{ij} a_{ij} \leq b_j \quad \forall j$$

$$d_{ij} = 0 \text{ or } 1$$

If this "upgraded" program provides a feasible solution we know that requirements which are elements of R_h and R_m will be satisfied at levels of .9 and .7 respectively and that all other requirements will at least be minimally satisfied. Once this iteration has taken place it is possible to examine the sensitivity of adding the R_m level of satisfaction constraints. If, for instance, we fail to find a feasible solution after the addition of the R_m constraints then we know that this infeasibility was caused by the addition of the constraints. We may also discover that by levying these constraints we have reduced the levels of satisfaction of the lower priority requirements (R_1) to such a level that resource allocation to them would not be worthwhile. We may also discover that the solution is satisfactory and continue onto the final iteration of the process which would be to add R_1 level constraints. At this point in time the program becomes identical to that shown at Equation 5.14.

There are many advantages to this iterative approach. It is extremely flexible and could easily be adapted to a wide variety of prioritization schemes. In the early stages of the iterative process there is a greater likelihood of finding a feasible solution to the problem because the constraints on the program are less severe than those associated with the formulation at Equation 5.14. However, a feasible solution to a problem formulated with such constraints (as alluded to in previous discussion) is not guaranteed. Additionally, this iterative process requires time and interaction with human decision makers.

k. Prioritization Using the Objective Function

Recall the term v_i in the objective function of the basic model. It was defined in the following manner:

v_i = The relative importance associated with a given collection requirement i .

In the previous model development we let v_i equal one for all i . In other words we considered all requirements to be of equal importance. In this portion of the model we have decided that all requirements are not of equal importance. Therefore, the objective function of the basic model considering requirement priorities would look very similar to the initial formulation:

$$\text{MAXIMIZE:} \quad E = \sum_{i=1}^n v_i E_i^2$$

$$\text{SUBJECT TO:} \quad \sum_{i=1}^n d_{ij} a_{ij} \leq b_j \quad \forall j$$

$$v_h = 1_1 \quad \forall R_h \quad (\text{eqn 5.17})$$

$$v_m = 1_2 \quad \forall R_m$$

$$v_l = 1_3 \quad \forall R_l$$

$$d_{ij} = 0 \text{ or } 1$$

l_i = A scalar representing the priority value of the i th requirement.

In this case the values of v_i would not all be equal to one.

There are numerous ways in which the values of v_i can be scaled. The most appealing method is to let the most important requirement in the set equal one and all others (in rank order) be values less than one but greater than zero. In the event many requirements were being considered in the set it may be wise to group those requirements of similar importance (i.e. in groups of high, medium, and low importance) and weight the groups appropriately. The effect of this sort of scheme is that the value of E is increased to a greater degree by higher priority (more heavily weighted) requirements than lower priority requirements. Thus, the program in its allocation process will emphasize the satisfaction of those requirements of higher priority. This type of formulation will lead to a feasible allocation solution to the model considering requirement priorities. However, once again we are uncertain as to the minimum levels of requirement satisfaction which will be obtained using such a formulation.

The problem of requirement priorities can be addressed through modification of the basic model in two basic manners - by adding constraints to the basic model, or modifying the objective function of the basic model. Each technique has its theoretical advantages and disadvantages. The usefulness of either approach would, therefore, be determined by the actual situation in which they might be applied.

3. Redundancy of Collection Coverage

Redundancy of collection coverage is an important collection management tool. It is often wise to insure that

at least two separate collection subsystems (or platforms) are tasked to satisfy certain important collection requirements. The model developed to this point in the discussion is unable to guarantee to the user that any quantity of subsystems other than one will be used to satisfy a given collection requirement. A method of handling this difficulty is to add additional constraints to the formulation. Once the decision maker has decided which requirements should be the subject of redundant coverage (R_r will indicate the subset of R which require redundant coverage) then restraints such as:

$$\sum_{j=1}^m d_{ij} \geq 2 \quad \forall i \in R_r \quad (\text{eqn 5.18})$$

could be added to the formulation outlined at Equation 5.14. One must remember that the more restraints which are added to a program decrease the chance of discovering an optimum solution and may decrease the quality of a feasible solution. Thus a more reasonable approach to the redundancy issue might also involve an iterative and interactive approach. For instance, once the user is satisfied with the resource allocations with respect to the priority of the set of collection requirements (as discussed in previous paragraphs), he might then examine those allocations to determine where redundancies of coverage already exist. Recall that an increase in levels of satisfaction (E_i^2) may be the result of the allocation of multiple collection subsystems. As a result, some of the collection requirements may already be satisfied by multiple subsystems in the existing feasible solution. Furthermore, those most likely to have such

multiple coverage are the more important requirements (from a priority point of view). If the decision maker is satisfied with the allocation scheme no further constraints need be applied to the program. However, if unsatisfied, the decision maker can apply constraints (such as those shown at Equation 5.18) in a piecewise fashion, compare new allocations with previous allocation schemes, and decide which set of resource allocations is better suited to the collection problem at hand.

4. Use of a Continuous Decision Variable

When we decide that the collection subsystems in the system can allocate collection resources in a continuous manner (as opposed to allocation of resources in discrete packages) then the continuous decision variable model described below is useful:

$$\text{MAXIMIZE:} \quad E = \sum_{i=1}^n v_i E_i^3 \quad (\text{eqn 5.19})$$

$$\text{WHERE:} \quad E_i^3 = \left(1 - \prod_{j=1}^m (1 - e_{(X_{ij})}) \right)$$

$$\text{SUBJECT TO:} \quad \sum_{i=1}^n x_{ij} \leq b_j \quad \forall j$$

$i = 1, \dots, n$ (i is the index for collection requirements. There are a total of n collection requirements considered in the requirement set of the model)

$j = 1, \dots, m$ (j is the index for collection subsystems. There are a total of m collection subsystems considered in the model)

x_{ij} = The amount of collection resource j allocated toward the satisfaction of collection requirement i (units are subsystem collection hours - hrs).

b_j = Total amount of subsystem j collection resources available for satisfying all collection requirements ($i = 1, \dots, n$).

v_i = Relative importance associated with requirement i (priority).

E_i^3 = Expected fraction of requirement i satisfied by all collection subsystems ($j = 1, \dots, m$).

There is a difference between this model and previous models developed in the study. Before, we were concerned with the management of collection resources given a way in which we were allowed to allocate each resource (a_{ij}). Thus, we were mixing fixed amounts of assets to obtain an optimal solution. In the continuous model we are managing not only the mix of assets but also the quantity of asset used in the mix. Thus, the continuous decision variable model should be viewed as a much more absolute model in terms of controlling the collection subsystems.

Because we are controlling how much of a given resource ought to be allocated toward the satisfaction of a given requirement the binary decision variable d_{ij} and the predetermined and fixed amount of collection resource

a_{ij} are not included in the continuous decision variable model. In their place we have introduced the continuous decision variable x_{ij} (defined above).

Because the amount of collection resource which can be allocated toward the satisfaction of a collection requirement is now variable we must re-evaluate the definitions of quantities which are dependent upon x_{ij} .

The e_{ij} term, previously defined for the discrete (basic) model was:

$$e_{ij} = p_{ij} \cdot f_{ij} \quad (\text{eqn 5.20})$$

It was interpreted to be the level of satisfaction with respect to requirement i we might expect to receive in the event collection resource j were allocated toward requirement i . In the discrete model situation a_{ij} was predetermined and fixed. In the continuous decision variable model, x_{ij} is a variable and thus p_{ij} , f_{ij} , and consequently e_{ij} are all functions of x_{ij} . The term $e_{(X_{ij})}$ is defined as follows:

$$e_{(X_{ij})} = P(X_{ij}) \cdot f(X_{ij}) \quad (\text{eqn 5.21})$$

$P(X_{ij})$ = The probability that collection subsystem j will collect the data it intends to collect in attempting to satisfy requirement i expending x_{ij} collection resources.

$f(x_{ij})$ = That fraction of requirement i which can be satisfied if collection subsystem j collects the data it intends to collect in attempting to satisfy requirement i allocating x_{ij} collection resources.

The expected fraction of requirement satisfaction ($f(x_{ij})$) is now a function of how much resource we allocate towards the satisfaction of a given intelligence requirement. Under most circumstances we would expect that the fraction of the requirement satisfied would generally increase (from some minimum value) to a maximum possible fractional level of satisfaction. It is hard to imagine a case in which more collection resource allocation would actually decrease the expected level of requirement satisfaction. Thus, this function is assumed to be monotonic nondecreasing.

The probability that a collection subsystem collects the data it intends to collect ($p(x_{ij})$) is also a function of x_{ij} . The possibility exists, given this functional relationship between $p(x_{ij})$ and x_{ij} , that the probability a collection subsystem collects the data it intends to collect may decrease as a function of x_{ij} . Consider the example of an aerial reconnaissance sortie over an enemy position (i.e. a threat exists to the survival of the platform). To increase x_{ij} (the amount of collection resource allocated) this platform may have to overfly the enemy position several times. In doing so the platform increases its vulnerability to the enemy threat and reduces its chances of returning its collected data to the subsystem operators. Thus, as the collection platform allocates more resources toward the satisfaction of the requirement its resulting $p(x_{ij})$ value decreases. Accordingly, the value of $e(x_{ij})$ which depends upon $f(x_{ij})$ could also decrease as x_{ij} increases. This

observation is difficult to interpret - as more collection resources are tasked toward the satisfaction of a requirement, the expected level of satisfaction of that requirement appears to decrease! There is a way around this difficulty. We can consider that the above example (and others similar to it) is not suited for use in a model using continuous decision variables. This assumption is fairly reasonable if we interpret (using the example above) each pass of the surveillance platform as a specific a_{ij} value (a discrete amount of collection resource) and that we must decide after each pass whether or not we want another one. This interpretation allows us to consider the aerial surveillance example with discrete rather than continuous decision variables.

The observations and discussion in the previous paragraph allude to the difficulty in interpreting the value $P(x_{ij})$ in the continuous decision model. Specifically, what type of collection subsystems (platforms) are suited to such a model and how do we determine $P(x_{ij})$ for an unknown x_{ij} ? The continuous decision model is best suited to those collection subsystems which are oriented towards a surveillance activity. In other words, those subsystems which monitor some form of enemy activity for a period of time (x_{ij} would therefore itself be a function of time on target - TOT). The requirements such subsystems might be tasked to collect information on would probably be somewhat time dependent. For instance, a SLR (side looking radar) might be asked to determine the direction of enemy advance. The probability that the SLR subsystem could determine that information would increase as TOT increased (and consequently x_{ij} increased). Determination of these sorts of $P(x_{ij})$ values would be difficult and probably could only be addressed with the use of empirical data or perhaps from a simulation.

In this model we are determining which collection subsystems ought to allocate resources to which requirements and also how much of those resources ought to be allocated towards the requirement. This is a fundamental difference from the basic (discrete) model. It (the continuous model) can be viewed as a relaxation of the basic model in that we are no longer concerned with collection resource packaging constraints but rather in allocating collection resources along a continuum.

VI. APPLYING THE INTELLIGENCE COLLECTION MANAGEMENT MODEL

A. INTRODUCTION

Three important assumptions were made in the development of the basic model. They were:

- Only a fixed number of collection requirements (n) could be considered in the model.
- Only a fixed number of collection subsystems (m) could be considered in the model.
- All requirements will have resources allocated toward their satisfaction at the same time.

With these assumptions we were able to develop a series of models which optimized the allocation of collection resources for a given set of collection requirements. The objective of this chapter is to illustrate how these assumptions are related to the realistic collection management environment and how the optimization models developed in Chapter Five can easily be modified to adapt to such an environment.

B. THE COLLECTION MANAGEMENT ENVIRONMENT

In the realistic collection management environment collection requirements enter the system, resources which seem suitable are tasked toward their satisfaction and if the requirements are satisfied they leave the system (other options are addressed in Chapter Two). Rarely, if ever, are collection requirements viewed in groups or sets as our models require. A multiserver queue would be a more apt description of the process.

Similarly, collection subsystems are rarely considered as a set. Either a subsystem available for tasking is suitable (can collect what the requirement indicates is necessary to collect) for satisfying (or at least partially) a requirement or it is not. If the subsystem is suitable it is tasked and if it is not suitable it is not tasked. On occasion, if there is sufficient justification, additional collection resources may be requested (and perhaps received) for use by the unit. Similarly, additional (and unplanned for) collection resources will sometimes be made available by a higher authority for use by the unit's collection system.

The entire allocation process is affected by time constraints associated with both the requirements and the collection subsystems (see Chapters Three and Four). The hectic pace of matching requirements with suitable and available platforms given a wide variety of deadlines rarely allows for more than a momentary consideration of the best allocation for a set of collection requirements.

It appears, therefore, that the assumptions we made in developing the optimization models counter our observations of the realistic collection management environment. The next section of this Chapter illustrates how, through a time analysis of all collection requirements and minor modification to the structure of the basic model, these problems can be easily overcome.

C. TIME ORDERING OF COLLECTION REQUIREMENTS

If our models are to be useful they must be adapted to the collection environment. To do this we must be able to identify, from the environment, those requirements which will be allocated collection resources. We know that the number of requirements in our imagined queue is variable and

dependent upon a variety of battlefield conditions. We also know that the requirement queue is not a FIFO (first in first out) or a LIFO (last in first out) queue but some sort of a mixed queue. We realize that we are more concerned with tasking resources to satisfy requirements whose tasking deadlines are in the near future rather than those whose deadlines are further into the future. At the same time, however, we do not want to squander our resources now without consideration for future requirements. These observations indicate that the number of requirements we want to consider in the our requirement set is somewhat time dependent.

This time dependency suggests that all intelligence requirements in the collection system can be ordered according to some time parameter. The time parameter of concern is what has previously been referred to as a tasking deadline. Consider a single collection requirement i in a collection system consisting of $j = 1, \dots, m$ collection subsystems. This requirement would have associated with it various time restraints (see Chapters Three and Four). Likewise, each collection subsystem would have associated with its resources various time restraints. If the time restraints associated with collection subsystem j were to be combined with the time restraints associated with collection requirement i then a tasking deadline (t_{ij}) could be identified.

t_{ij} = The tasking deadline associated with requirement i and subsystem j . That point in time beyond which subsystem j cannot be tasked to satisfy requirement i .

If we are considering a total of m subsystems (all of which could contribute to the satisfaction of requirement i) and none of the time restraints associated with those subsystems

were identical then there would exist a maximum of m tasking deadlines associated with requirement i . We are concerned with identifying that t_{ij} value which, if met, would not exclude the use of any of the subsystems which can contribute to the satisfaction of requirement i from doing so. That value will be referred to as t_{ci} :

t_{ci} = The latest point in time such that all subsystems which can contribute to requirement i can be tasked to do so.

or, given that all t_{ij} values fall along the interval from $t = 0$ to t , then t_{ci} can be defined in the following manner:

t_{ci} = That value of t_{ij} which produces the minimum value of the expression:

$$(t_{ij} - t_0) \quad \forall j \quad (\text{eqn 6.1})$$

Thus, t_{ci} might be referred to as a global tasking deadline for requirement i .

The purpose of defining t_{ci} was to identify a reasonable means of ordering collection requirements according to time. The t_{ci} values can easily be determined for each collection requirement in the collection system. Note that t_{ci} values are entirely dependent upon the collection subsystems (their time restraints) available for tasking by the collection system (actual and envisioned). In the event additional (and not envisioned) collection subsystems were made available to the collection system then t_{ci} values could easily be recalculated.

We are still faced with the question of how to determine which set of requirements will be included in the model. That determination will be based upon a close examination of the time ordered set of requirements. We would like to include all requirements in the model. This, however, may be unreasonable if the range of t_{ci} values is great (i.e. greater than 12 hours). This is primarily due to the fact that we just aren't that concerned with requirements whose tasking deadlines are far into the future. Requirements whose t_{ci} values fall within the zero to eight hour range seem more appropriate for inclusion in the model. This determination, of course, could change according to a variety of possible battlefield conditions. We will call this time range of interest t_{int} , where:

t_{int} = That time interval in which we are concerned with tasking collection resources toward the satisfaction of intelligence requirements.

The requirements which fall within this range of interest (t_{int}) constitute a subset of n (the total number of requirements in the collection system) and will be defined in the following manner:

\bar{n} = The time ordered subset of the total number of collection requirements (n) which fall within t_{int} .

Thus, \bar{n} is that subset of the total number of collection requirements in the collection system which we are, in the short run, interested in satisfying. We have, therefore, reduced the number of requirements to be considered in our models to those of more immediate interest. The basic model can easily be modified to adjust for the change in values of n :

$$\begin{aligned}
 &\text{MAXIMIZE:} && \sum_{i=1}^{\bar{n}} v_i E_i \\
 &\text{SUBJECT TO:} && \sum_{i=1}^{\bar{n}} a_{ij} d_{ij} < b_j \quad \forall j \\
 &&& d_{ij} = 0 \text{ or } 1
 \end{aligned}$$

This modification can be applied to all other models developed in Chapter Five.

As alluded to in previous discussion \bar{n} is primarily based upon the determination of t_{int} . The range of t_{int} , however, is quite subjective and variable. Thus, we can look upon \bar{n} as a variable. We have shown that the models developed in Chapter Five can be modified to include \bar{n} and they therefore appear to be useful in realistic applications where the number of collection requirements under consideration is variable. Furthermore, we have, by time ordering the set of collection requirements, expressed those requirements as a function of time - the first step toward a more realistic piecewise collection resource allocation process.

D. ALLOCATING COLLECTION RESOURCES

An assumption of the basic model was that all collection requirements under consideration will have collection resources allocated toward their satisfaction at the same

time. An examination of the realistic setting clearly indicates that this assumption is unreasonable. The previous section developed a requirement scheduling method which would help the decision maker determine which collection requirements in the collection system the optimization models ought to include. A reasonable approach toward allocating collection resources is to allocate (based upon the output of the optimization model) only to those requirements whose t_{ci} values are near, update the model with respect to current conditions (new incoming requirements, modified amount of resources available, and new t_{ci} values), and optimize over the new set of conditions. The allocation process would look like that shown in Figure 6.1.

This allocation process allows for the variation of the amount of collection resources considered in the optimization models and for the piecewise allocation of such resources toward the satisfaction of collection requirements. The success of this process, however, is dependent upon several factors. A factor of primary importance is whether or not the optimization model employed in the process can provide a feasible allocation plan in a timely manner. Additionally, we are assuming that necessary inputs (updates of current conditions) can be provided to the process.

It is important to note that the models can be applied to situations in which the amount of available resources are variable and actual resource allocations are made in a piecewise fashion. This is accomplished by embedding the optimization model in an iterative allocation process rather than through any modification of the actual model.

The optimization models developed in Chapter Five appear to be more flexible than initially envisioned. They can be adapted to the more realistic collection management setting in which both requirements and resources are variable and

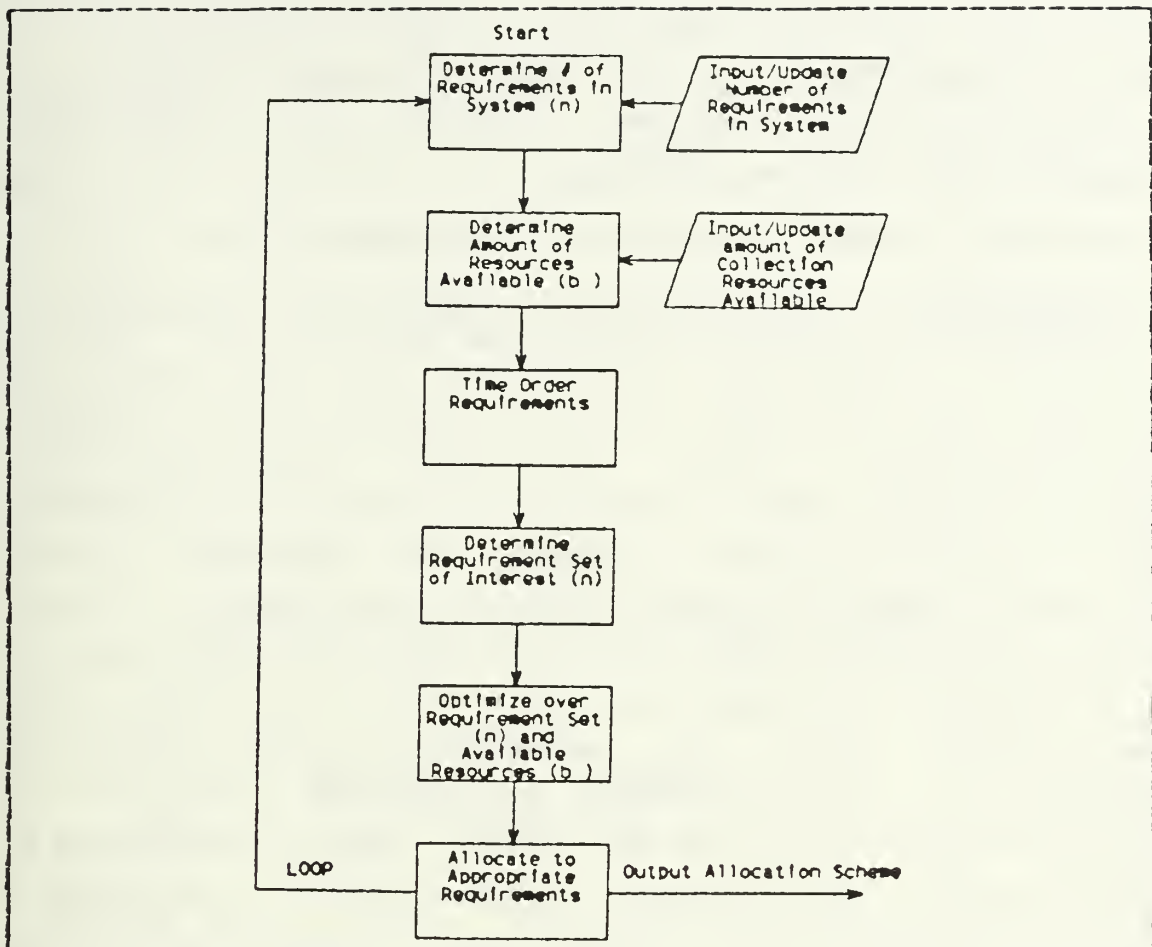


Figure 6.1 Collection Resource Allocation Process.

collection allocations are made only when required (and in accordance with the current battlefield situation).

E. SIZE OF THE OPTIMIZATION MODEL

It is important to estimate the size of the collection management problem. In particular we would like to know how many collection subsystems and requirements will be considered in the optimization models developed in Chapter Five. An estimation of this nature is dependent upon the echelon of friendly force of interest. This study will, therefore,

focus on the maneuver division in estimating the size of the various components of the collection management problem.

The collection subsystems available to a division generally fall into two classes:

- organic: Those belonging to the division.
- non-organic: Those which the division can (in certain situations) task for use but do not own.

Divisions are virtually free to operate their organic subsystems (IMINT, SIGINT, and HUMINT) in accordance with their battlefield role or mission. However, the division will be granted access to non-organic subsystems (which correspond closely to those found at the division but are usually more specialized) only when its battlefield mission is of relative importance (i.e. the unit is in contact with enemy forces). Thus, the number of collection subsystems available to a division varies (primarily as a function of its battlefield role) from an organic number of three to a maximum number (both organic and non-organic) of twelve. The availability of both organic and non-organic collection subsystems is also dependent upon environmental and operational factors (primarily weather and threat). These factors would, of course, reduce the total number of subsystems available to the division.

An intelligence system of a division is normally concerned with approximately 15 to 30 standing intelligence requirements (referred to as Essential Elements of Information and Other Intelligence Requirements - EEI/OIR) and perhaps 15 to 30 user generated intelligence requirements. Each of these intelligence requirements are vague and can be decomposed into several collection requirements (i.e. the SIGINT collection subsystem would refer to these collection requirements as SIGINT Indicators). The number of collection requirements in the collection system is also

somewhat dependent upon the battlefield role and disposition of the division. One would expect that the number of requirements would increase as more organic forces are brought into contact with the enemy. Given a particular battlefield situation, the number of collection requirements we would expect to encounter would fall between 30 and 200.

Given this discussion it is possible to address the range of the collection management problem. Estimates of the maximum size and minimum size problems can easily be

TABLE I
Size of the Collection Management Problem

	<u>Levels</u>	
	<u>Maximum</u>	<u>Minimum</u>
<u>Reqs</u> (r)	250	30
<u>Subsys</u> (s)	12	3

provided: The implications of these estimated values are interesting. For example, in the discrete decision (basic) model under maximum conditions ($n = 250$ and $m = 12$), there would exist 3000 (250×12) decision variables (d_{ij} in the discrete model, x_{ij} in the continuous model) to consider. This assumes, of course, that each collection subsystem is capable of contributing to the satisfaction of each collection requirement. The point to be made is that the complexity of the problem increases dramatically as more

collection subsystems and requirements are added to the collection system. This observation highlights the need for us to consider all reasonable methods of reducing the complexity of the problem (such as the reduction of the set of requirements n to \bar{n} as discussed in Section C of this Chapter).

F. CONCLUSIONS AND RECOMMENDATIONS

This thesis has developed a structure for and examined the functions of a generalized intelligence collection system. Traditional approaches toward the management of collection requirements (identified in the study as the primary focus of the collection system) were shown to be inefficient and less controlled than desired. It was also shown that with minor restructuring of some functions within the collection system and development of the capability to estimate subsystem operational capability components (p_{ij} and f_{ij}), operations research techniques could be applied to a simplified version of the collection system problem, that being the allocation of scarce collection resources toward the satisfaction of collection requirements.

A mathematical optimization model of this simplified process was developed. Modifications of this model were explored with respect to important intelligence collection related concepts such as priority of requirements, redundant collection coverage, and applicability of the optimization model to various types of collection subsystems.

Future efforts in this area should focus on the following topics:

- Solution algorithms to the models developed in Chapter Five.
- Use of the models as decision aids in wargames and as resource allocation algorithms in battlefield simulations.

- The classification of intelligence collection requirements in terms of the ^{ij} methodology developed in Chapter Five.

APPENDIX A

A METHOD OF RANKING COLLECTION REQUIREMENTS

Collection systems have traditionally prioritized collection requirements according to SOP's. Each unit's SOP is different from another. They all, however, prescribe what a requirement priority will be given the existence of certain conditions on the battlefield. For example, an SOP may require that collection requirements from support units (non-combat forces) cannot be submitted as high priority requirements. The battlefield condition in this example is the nature of the friendly unit submitting the requirement.

Collection requirements are rarely analyzed in groups. Thus, once a requirement (and its priority as determined by the SCP) are validated (approved by the collection system decision maker) they are forwarded for action to the collection subsystems. In the restructured approach discussed in this thesis a set of collection requirements are decomposed at the system level prior to being forwarded to the collection subsystems for action. Thus, it is feasible at the system level to analyze a set of requirements with respect to priority. Specifically, it is possible to re-prioritize this set of collection requirements with respect to the current battlefield conditions rather than those which may have existed when the collection requirement was initially submitted for satisfaction by the user.

This approach recognizes the fact that battlefield conditions change and that the relative importance of one requirement with respect to another might also change. In this study the battlefield conditions previously addressed will be referred to as battlefield parameters of interest or simply parameters.

The objective of this process is to rank all requirements under consideration based upon one or several of the battlefield parameters of interest. In effect, this process provides the decision maker with a method of prioritizing requirements in accordance with the current or projected battlefield conditions. A multi-criteria aggregation scheme will be used to rank the set of collection requirements.

A. THE REQUIREMENT RANKING MODEL

The model for the requirement ranking process is described below:

$$\text{MAXIMIZE:} \quad \sum_{k=1}^l w_k \text{Par}_{ik} \quad (\text{eqn A.1})$$

i = The index for requirements.

k = The index for parameters.

l = The total number of battlefield parameters.

w_k = Weighting associated with the k th parameter.

par_{ik} = The k th battlefield parameter associated with the i th requirement.

There are a number of ways in which this scheme can be implemented through the specific allocation of weights to a particular set of parameters.

E. BATTLEFIELD PARAMETERS

Four general battlefield parameters of interest will be addressed in this study. These four categories of parameters are not all inclusive. Virtually any parameter of interest to the unit or command (depending upon the requirement structure) could easily be substituted for or added to those addressed in the study. These are, however, representative of the basic concerns of battlefield decision makers.

The first parameter addressed is the actual priority attached to the requirement. The requirement priority is provided by the user when it is initially submitted into the collection system for satisfaction. It will be assumed that priority reflects the importance of a requirement to the user with respect to all other collection requirements submitted in accordance with the priority system (abuses of priority systems will not be addressed). For example, it will be assumed that all high priority requirements are of greater relative importance to all users than all medium priority requirements, etc. There are many different types of priority systems in use. Most of these systems attempt to classify items in terms of levels of importance (priority). Such classification schemes can, in themselves, become complex. Only three levels of priority will be considered in this study - high, medium, and low.

The friendly unit submitting the requirement is the second parameter of interest. As the battlefield changes, so does the relative importance of friendly units. This importance is reflected in the amount of support a command receives from its parent and supporting units. This includes intelligence collection support. It is therefore important to be able to reflect this changing importance when ranking collection requirements. The number and type of units included as varieties of this parameter are, of

course, dependent upon the organization operating the collection system. A Corps, for example, may want to include its covering force, major maneuver divisions, and artillery forces in this category of parameters. This study will focus at the Division level and will, therefore, include as its friendly units of interest the primary users of its collection system - two maneuver units (number 1 and number 2), an artillery unit, and a headquarters element.

The area of the battlefield in which the requirement is focused is the third parameter or interest. The identification of where the enemy may be attacking from is a traditional concern to the military decision maker. Thus, the ability to control collection with respect to battlefield area is one method of coping with this concern. This parameter is initially provided by the user when submitting the collection requirement. However, between requirement submission and the collection allocation decision there is a possibility that this parameter might change. For example, an enemy unit originally located in the rear area of the battlefield may have moved forward by the time a collection requirement concerning that unit can be acted upon. Thus, the status of this parameter should be updated by the system operators prior to the collection allocation decision. Four battlefield areas will be used in this report (see Figure A.1). Areas I and II represent those areas in contact with friendly forces (FLOT stands for the front line of troops) while areas III and IV represent the enemy rear areas. Traditionally, fighting units are primarily concerned with threats in the forward areas I and II. Headquarters elements and interdiction forces are more interested in targets and enemy activities in the rear areas III and IV.

Enemy activity is the last battlefield parameter of interest to be considered. Different battlefield users of the collection system are concerned with different forms of

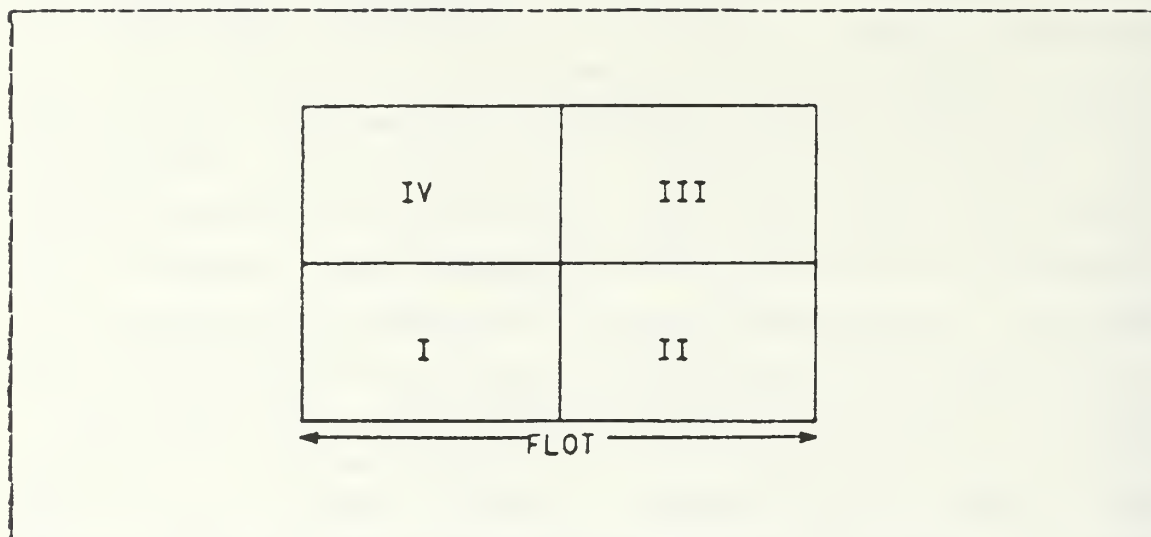


Figure A.1 Battlefield Areas.

enemy activity. Maneuver units tend to be concerned with enemy maneuver and artillery forces, support units with special operation forces, headquarters elements with interdiction targets and command and control operations. These concerns, of course, vary as the battlefield situation varies. Thus, timely control of the type of enemy activity the collection effort is directed against is valuable. For illustrative purposes the study considers four such classes of enemy activity - maneuver forces, artillery forces, support forces, and C3/other forces. Table II summarizes the major classes, levels, and subclasses of the fifteen parameters mentioned.

C. BATTLEFIELD PARAMETER VALUES

In this scheme two of the classes of parameters associated with a given requirement have no particular values associated with them other than presence or absence (with associated values of either one or zero). For instance, a requirement can have either a high, medium, or low priority.

TABLE II
Levels and Classes of Requirement Parameters

CLASS	LEVEL	SUBCLASS
Priority	High Medium Low	
Friendly User		Maneuver Unit 1 Maneuver Unit 2 Artillery Unit Headquarters Element
Battlefield Area		I II III IV
Enemy Activity		Maneuver Forces Artillery Forces Support Forces C3/Other Forces

This characteristic is also valid with respect to the friendly unit submitting the requirement. It does not necessarily apply to the parameter classes of battlefield area or type of enemy activity. It is conceivable in these cases that varying degrees of values could be associated with more than one parameter of the class. For instance, a requirement regarding the communications capability of an enemy artillery unit would fall into both the C3 and artillery parameter classes. Likewise, a requirement could easily be associated with more than one area of the battlefield. These sorts of evaluations would be provided by the user and perhaps modified by the collection system operator with the aid of standard operating procedures.

D. WEIGHTING OF BATTLEFIELD PARAMETERS

TABLE III
Requirement Parameter Weighting Schemes

PARAMETER	WEIGHTING SCHEMES			
	I	II	III	IV
Priority (h)	.5	.2	-	-
Priority (m)	.3	-	-	-
Priority (l)	.2	-	-	-
Unit 1	-	.3	-	-
Unit 2	-	-	-	-
Arty Unit	-	.3	-	-
HQ Element	-	.2	-	-
Area I	-	-	.2	-
Area II	-	-	.2	-
Area III	-	-	-	.2
Area IV	-	-	-	.2
Maneuver Force	-	-	.3	-
Arty Force	-	-	.3	-
Support Force	-	-	-	.3
C3/Other	-	-	-	.3

Table III illustrates several battlefield parameter weighting schemes. Weighting scheme number I can be referred to as a standard scheme. The ranking of requirements using this scheme is based solely upon the priority of the submitted requirements. Scheme number II can be referred to as a support scheme. Collection requirements will be ranked based upon the friendly unit submitting the requirement with some emphasis placed upon priority. Specifically, maneuver unit number one and the artillery

unit are favored over the headquarters element. The HQ is, in turn, weighted equally with high priority requirements. The purpose behind this sort of weighting scheme would be to provide collection support to specific units because of their importance in relation to the current or projected battlefield situation.

The last two weighting schemes are oriented towards targeting. Scheme III, for instance, is weighted to support requirements concerning enemy combat force targets (maneuver and artillery forces) near friendly forces (in battlefield areas I and II). This scheme could be referred to as a direct support targeting scheme. Scheme IV, on the other hand, is oriented towards targets in the enemy rear area (battlefield areas III and IV) and of a soft nature (C3 and Support Elements). This scheme could be referred to as an interdiction targeting scheme. If the decision maker were interested only in enemy artillery forces in battlefield area II then only those two parameters should be weighted (.5 in each case because there are two parameters of interest). If there exist such targets in the requirement set then they will be the highest ranking targets in the ordered requirement vector.

The quantity, variety, and resolution levels of possible weighting schemes are uncountable. This methodology would be particularly useful to the decision maker in the event he was required to rank a large number of collection requirements.

E. AN EXAMPLE USING THE REQUIREMENT RANKING MODEL

Table IV presents a set of twenty sample collection requirements which were generated to demonstrate the multi-criteria approach to collection requirement ranking. Note that in Table IV the values for the first two groups of

parameters (priority and friendly unit) are merely a one or and dash. The one signifies a yes and the dash signifies a no. In other words requirement number 1 has a high priority and was submitted by the friendly artillery unit.

The values associated with the second two groups of parameters (battlefield area and enemy activity) are expressed as percentages. Requirement number one, therefore, is concerned with enemy combat and artillery forces in the forward two areas of the battlefield (Areas I and II).

Much of this information is provided by the user when submitting a requirement for satisfaction. Traditionally, however it has been forwarded in subjective rather than numerical form. Thus, the success of this sort of a prioritization scheme would be contingent upon the ability of the battlefield to satisfactorily estimate the appropriate parameters in a numerical manner.

TABLE IV
Sample Collection Requirements

Parameter	<u>Requirement Number</u>																			
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
High	1	1	1	1	-	-	1	-	1	1	-	1	1	-	-	1	1	1	-	-
Medium	-	-	-	-	1	-	-	1	-	-	1	-	-	1	-	-	-	-	1	1
Low	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Unit I	-	-	1	1	-	-	1	-	-	-	-	1	-	-	-	-	1	-	1	-
Unit II	-	-	-	-	-	-	-	-	-	-	1	-	-	1	-	-	-	-	-	-
Unit	1	-	-	-	1	1	-	-	1	-	-	-	1	-	-	1	-	1	-	-
Arty	-	-	-	-	-	-	-	-	-	1	-	-	-	-	-	-	-	-	-	-
HQ	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Area I	.5	-	.5	.5	-	.5	1	.3	.5	.1	.5	.5	-	-	-	-	1	.5	.5	.5
Area II	.5	-	.5	.5	-	.2	-	.3	.5	.1	.5	.5	-	-	-	-	-	-	-	-
Area III	-	.5	-	-	.5	.3	-	.2	-	.4	-	-	.5	.5	.5	.5	-	.3	.5	-
Area IV	-	.5	-	-	-	-	-	.2	-	-	-	-	.5	.5	-	-	-	.2	.5	-
Comlat	.5	1	-	.5	-	.3	1	-	.5	.1	.5	.5	-	-	.3	-	1	.5	.5	.5
Arty	.5	-	.5	.5	-	.2	-	-	.5	.1	.5	.5	-	-	.3	-	-	-	-	.3
Support	-	-	.5	-	.5	.3	-	-	-	.4	-	-	.5	.5	.5	.4	-	-	.5	-
C3	-	-	-	-	.5	.3	-	1	-	.4	-	-	.5	.5	.4	1	-	.5	-	-

These requirements were placed into an APL usable format using the program READREQ. This is an interactive program which queries the operator for a collection requirement vector (Figure A.2). The input values for this vector are shown at Table V.

```

▽ A1←READREQ;V;V1;RHO;S
[1]  V1← 1 16 f0
[2]  ONE: 'ENTER 16 COMPONENT REQUIREMENT VECTOR: '
[3]  V←0
[4]  V1←V1,[1] V
[5]  RM←V1
[6]  'FINISHED? (YES/NO): '
[7]  S←0
[8]  →STOP×13=+/'YES'=3f5
[9]  →ONE
[10] STOP:
[11] RHO←(1↑(PRM))-1
[12] RM←(RHO,16)f(16↓,RM)
[13] A1←RM
▽

```

Figure A.2 Requirement Input Program READREQ.

READREQ formats the n collection requirements in matrix form which can be operated upon by the APL program ICALC. ICALC uses the model addressed previously to rank the requirements which were submitted by the operator using READREQ. The output of ICALC is the a rank ordered requirement vector.

Table VI illustrates how the weighting schemes discussed in an earlier portion of this appendix rank the set of sample requirements presented at Table IV. Note the requirement order for Scheme I (recall that this was referred to as the standard scheme which basically ranks requirements according to their user provided priority). The first eight requirements in Scheme I (1 through 18) are

TABLE V
BEADREQ Entry Data

<u>Vector Element</u>	<u>Component</u>	<u>Value Format</u>
1	Requirement Number	1 to 20
2	Priority (High)	0 or 1
3	Priority (Medium)	0 or 1
4	Priority (Low)	0 or 1
5	Friendly Unit I	0 or 1
6	Friendly Unit II	0 or 1
7	Artillery Unit	0 or 1
8	Headquarters Element	0 or 1
9	Battlefield Area I	0 to 1
10	Battlefield Area II	0 to 1
11	Battlefield Area III	0 to 1
12	Battlefield Area IV	0 to 1
13	Enemy Maneuver Force	0 to 1
14	Enemy Artillery Force	0 to 1
15	Enemy Support Force	0 to 1
16	Enemy C3/Other Force	0 to 1

the same requirements which Table IV indicates have a priority of one. The next eight requirements (3 to 19) have a priority of two and the last four (5 through 20) have a priority of three. In Scheme II the requirement order is based upon the unit submitting the requirement and the priority. A look at the higher ranking requirements associated with Scheme II does indicate that they are a function of being high priority and/or from Unit 1, the artillery unit or the headquarters element. Similar analysis of


```

      ▽ I CALC; RHO; N; W; WM; XBAR; XM; SDM; XRM; NXRM; SXRM
[1]   RHO←F(RM)
[2]   N←20
[3]   'ENTER 16 COMPONENT WEIGHT VECTOR'
[4]   W←0
[5]   RW←16F(÷16)
[6]   WM←(RHO)FW
[7]   XBAR←(+√RM)÷N
[8]   XM←(RHO)FXBAR
[9]   XRM← 0 1 ↓(WMXRM)
[10]  SXRM←+√XRM
[11]  NXRM←Q(2 20)P((1N),(,SXRM))
[12]  OREQ←NXRM[φNXRM[;2];]
[13]  'REQUIREMENT RANKING'
[14]  RE←OREQ[;1]
[15]  RE
[16]  AMX←AM,NXRM[;2]
[17]  AMX[;2]←AMX[;2]xAMX[;3]
[18]  AMX[;5]←AMX[;5]xAMX[;6]
[19]  AMX[;8]←AMX[;8]xAMX[;9]
[20]  AMX←AMX[φAMX[;11];]
      ▽

```

Figure A.3 Multi-Criteria Requirement Ranking Program.

Schemes III and IV reveals that they do indeed rank the given set of collection requirements in the manner suggested by their respective weighting schemes. Specifically, Scheme III is oriented towards enemy combat arms forces in the forward areas of the battlefield and Scheme IV is oriented towards support and C3 forces located in the rear areas of the battlefield.

One additional point for consideration regards the complexity of the requirement weighting schemes. This model will rank collection requirements according to even the most intricate of weighting schemes. It is difficult, however, to understand the output of such complicated schemes. Simple schemes are easy to check and also useful in sorting out a difficult collection management problem. This portion of the model is presented as a decision aid to allow for

TABLE VI
Requirement Ranking with Weighting Schemes

<u>Original Requirement Order</u>	<u>Weighting Schemes</u>			
	<u>I</u>	<u>II</u>	<u>III</u>	<u>IV</u>
1	1	1	7	16
2	2	7	17	5
3	7	9	1	13
4	9	12	4	14
5	12	17	9	15
6	16	16	11	10
7	17	18	12	8
8	18	3	20	6
9	3	5	3	18
10	4	6	2	19
11	6	15	6	2
12	10	19	18	3
13	11	2	19	20
14	13	8	8	1
15	15	10	10	4
16	19	13	15	7
17	5	4	5	9
18	8	11	13	11
19	14	14	14	12
20	20	20	16	17

improvement of current techniques in managing collection requirements which have traditionally employed FIFO (first

in first out) methods. As such, it should be used to simplify the work of the decision maker rather than make it more difficult.

BIBLIOGRAPHY

Applications of Artificial Intelligence Tools and Techniques to SIGINT Analysis and Sensor Management. Sunnyvale: ESI, 1983.

Ashby, W. Ross. An Introduction to Cybernetics. New York: John Wiley and Sons, Inc., 1956.

Buchanan, Bruce G. and Duda, Richard O. Principles of Rule-Based Expert Systems - Heuristic Programming Project Report No. HPP-82-14. Stanford: Stanford University Press, 1982.

Ching-Lai Hwang and Abu Syed Md. Masup, Multiple Objective Decision Making - Methods and Applications. Lecture Notes in Economics and Mathematical Systems, No. 164. New York: Springer-Verlag, 1979.

Fishburn, Peter C. Decision and Value Theory. New York: John Wiley and Sons, Inc., 1964.

Gribble, G Dickson. "Collection Management: Intelligence Support to the Air-Land Battle." Research paper submitted for the Army Command and General Staff College, Ft. Leavenworth, KS, 1984.

Lee, Alec M. Systems Analysis Frameworks. New York: John Wiley and Sons, Inc., 1970.

Lesson Plan: Intelligence Collection Management. Ft. Huachuca, AZ: USAICS, 1980.

Mesarovic, Mihajlo D. "On Vertical Decomposition and Modeling of Large Scale Systems." In Decomposition of Large Scale Problems, pp. 323 - 340. Edited by David M. Himmelblau. Amsterdam: North-Holland Publishing Company, 1973.

Methlie, Leif B. Information Systems Design. New York: Columbia University Press, 1978.

Monterey, CA. Naval Postgraduate School. Lecture notes from a course in Decision Theory given by Dr. Glenn F. Lindsay, 1984.

Monterey, CA. Naval Postgraduate School. Lecture notes from a course in Non-linear and Dynamic Programming by Dr. James K. Hartman, 1984.

Saaty, Thomas L. The Analytical Hierarchy Process. McGraw-Hill, Inc., New York, 1980.

Shepard, Roger N. "On Subjectively Optimum Selection Among Multiattribute Alternatives." In Human Judgements and Optimality, pp. 257-279. Edited by Maynard W. Shelly, II and Glenn L. Bryan. New York: John Wiley and Sons, Inc., 1964.

Starr, Martin K., and Greenwood, Leonard H. "Normative Generation of Alternatives with Multiple Criteria Evaluation." In Multiple Criteria Decision Making, pp. 111-127. Edited by Martin K. Starr and Milan Zeleny. New York: North-Holland Publishing Company, 1977.

Waltz, Frederick M, "An Engineering Approach: Hierarchical Optimization Criteria," IEEE Transactions on Automatic Control, AC-12, No. 2 (1967): 179-180.

Zeleny, Milan. Multiple Criteria Decision Making. New York: McGraw-Hill Book Company, 1982.

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